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Identifying Quantitative and Qualitative Monetary Policy Shocks*

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This paper proposes a method for identifying quantitative and qualitative monetary policy shocks in the balance sheet operations of a central bank in VAR analysis. The method is agnostic and flexible, as it relies on no assumptions on how the size and composition of the central bank's balance sheet will respond after the bank makes a policy decision. We identify two types of policy shocks as "anticipated" shocks that best portend the current and future paths of these policy instruments in response to them. We obtain evidence that qualitative easing shocks have expansionary effects on the economy while quantitative easing shocks do not.

JEL Codes: E52, E58.

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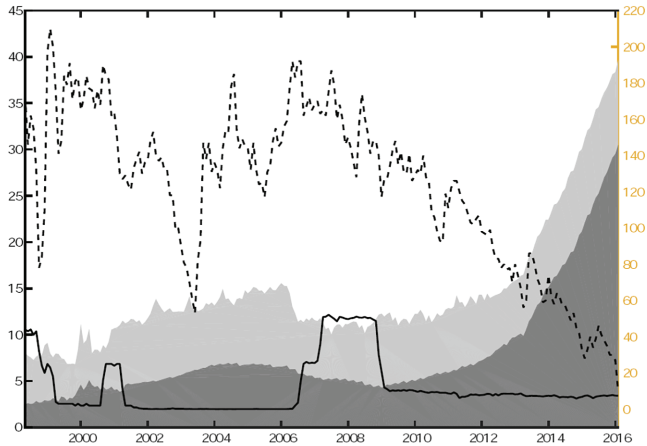
1. Introduction

In this paper, we introduce a novel identification approach to disentangle the causal effects of the Bank of Japan (BOJ)'s quantitative and qualitative monetary policy shocks in its balance sheet operations. More specifically, our new strategy addresses two issues entailed in identifying the unconventional monetary policy shocks in the vector autoregressive (VAR) analysis: the endogeneity of the monetary policy indicators, and quantitative and qualitative monetary policy shocks as "anticipated" shocks. By identifying quantitative and qualitative monetary policy shocks, we provide robust evidence that the quantitative easing shock, the shock that increases the size of the BOJ's balance sheet, significantly decreases the long-term nominal interest rate without conferring any favorable effects on real economic activity. Specifically, the impulse response analysis shows that a quantitative shock that increases the monetary base by 10 percentage points, in the long run, has slightly negative effects on the output gap, inflation rates, and stock prices although it significantly decreases 10-year government bond yield as well as short-term rates. On the other hand, the qualitative easing shock, the shock that increases the BOJ's unconventional asset ratio to its total assets, brings about expansionary effects. We find that a qualitative easing shock of increasing the unconventional asset ratio by 0.3 percentage point stimulates the output gap by 0.1 percentage point and the inflation rate by 0.4 percentage point while significantly increasing stock prices. Also, we show some suggestive evidence that the quantitative easing shock causes a negative effect because it has a signaling effect regarding the future path of the economy. Finally, we find that the conventional easing monetary policy shock, the increase in the short-term policy rate, has an expansionary effect even in the low interest rate period.

Central banks have several monetary policy options, even with the policy rate at an effective lower bound (Bernanke and Reinhart 2004). For example, in March 2001, the BOJ adopted a quantitative easing policy by setting the targeted overnight call rate to almost 0 percent. Under this policy framework, the monetary base, or size of the BOJ's balance sheet, expanded through the growth of excess reserves in the BOJ's current account bases (see Figure 1). The BOJ discontinued its quantitative easing policy in March 2006 but

Figure 1. Size, Unconventional Assets, Call Rate, and Long-Term Bond Yield



Note: The dark gray and light gray shadows indicate the amounts of unconventional assets and conventional assets held by the Bank of Japan, respectively. The amounts are shown in units of 10 trillion yen on the left-hand scale. Unconventional assets include exchange-traded funds (ETFs), real estate investment trusts (REITs), corporate bonds, commercial paper, long-term government bonds, and asset-backed securities. Conventional assets include other assets such as short-term government bonds. The plotted line represents the call rate, while the dashed line corresponds to the 10-year Japanese government bond yield, both in basis points on the right-hand scale.

has kept the targeted rate well below 0.5 percent since then. In its quantitative and qualitative easing (QQE) policy introduced in April 2013, the BOJ further deepened its unconventional policy framework not simply by enlarging its balance sheet, but by increasing the ratio of unconventional assets, such as long-term Japanese government bonds (JGBs) and risk assets (e.g., exchange-traded funds (ETFs) and real estate investment trusts (REITs)), on its balance sheet.[1] Central banks in advanced economies such as the United Kingdom, United States, and euro-area countries have followed with their own unconventional policy frameworks characterized by similar increases in the sizes of the central bank balance sheets and changes in the

[1]See Shiratsuka (2010) and Ueda (2012) for a detailed explanation of unconventional assets in Japan.

balance sheet compositions at extremely low policy-targeted interest rates.

While the actual implementation of the unconventional monetary policy in many countries has stimulated empirical research on unconventional policy effects using the structural VAR model, the policy effects on the real economy are still disputable.[2] One of the biggest challenges in assessing unconventional policy effects by VAR analysis is the choice of variables to use as monetary policy indicators that precisely reflect the central bank's policy decisions in the unconventional monetary policy. Starting from the premise that monetary aggregates such as the monetary base and excess reserves represent a central bank's policy stance, several previous studies have used reduced-form VAR innovations of those variables as exogenous components of the unconventional monetary policy (Iwata and Wu 2006, Inoue and Okimoto 2008, Honda, Kuroki, and Tachibana 2013, Kimura and Nakajima 2016, Miyao and Okimoto 2017, and Hayashi and Koeda 2019).[3] This empirical strategy is essentially an extension of the standard recursive VAR approach to estimate the effects of the conventional monetary policy of controlling short-term nominal interest rates (Bernanke and Blinder 1992 and Christiano, Eichenbaum, and Evans 1996).[4]

Other empirical studies on unconventional policy effects have employed a strategy that does not require one-to-one mapping between an observable monetary policy indicator and a monetary policy shock. By assuming that unconventional monetary policy shocks can be represented collectively as a single unobservable shock, they apply a VAR analysis that imposes sign restrictions on the impulse responses of the macroeconomic variables to single monetary policy shocks (Kapetanios et al. 2012, Baumeister and Benati

[2]See Ugai (2007) and Joyce et al. (2012) for a survey of the empirical research on unconventional policy effects.

[3]Previous studies applying the recursive VAR approach to unconventional monetary policy in the United Kingdom and United States have not necessarily used the monetary base or excess reserves as an unconventional monetary policy indicator. Wu and Xia (2016), for example, used shadow policy rates for an analysis of the United States, and Weale and Wieladek (2016) used asset purchase announcements for analyses of the United Kingdom and United States.

[4]Rudebusch (1998) and Nakamura and Steinsson (2018) discuss concerns underlying the use of the standard recursive VAR approach to identify monetary policy shocks.

2013, Schenkelberg and Watzka 2013, Gambacorta, Hofmann, and Peersman 2014, and Weale and Wieladek 2016)[5] and heterogeneous variance restrictions on the intensity of structural shocks, including single policy shocks (Wright 2012, Rogers, Scotti, and Wright 2014, and Shibamoto and Tachibana 2017).[6]

However, since central banks utilize different policy tools in the low interest rate environment, the two aforesaid empirical strategies are insufficient to assess the effects of unconventional policy. In the case of Japan, the BOJ has purchased a vast range of different financial assets such as exchange trade funds, commercial papers, and long-term government bonds. To address this issue, we assume that the unconventional monetary policy implemented by the BOJ in its balance sheet operations has two aspects: a *quantitative* and a *qualitative* easing.[7] In this paper, we propose a method for identifying the BOJ's quantitative and qualitative monetary policy shocks in VAR analysis.

Another identifying issue is how monetary policy indicators respond to policy changes. As discussed above, previous studies on unconventional policy effects based on VAR analysis have taken either of two approaches. Some have regarded reduced-form VAR innovations of monetary aggregates such as the monetary base as unconventional policy shocks. Others have imposed restrictions on the impulse responses of some of the variables to a single unobserved unconventional policy shock. Regardless of the difference in methodology, both of these approaches assume that all monetary policy shocks to monetary aggregates are "unanticipated," and both approaches provide evidence that unconventional policy shocks yield

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[5] A naive sign restriction would fail to extract any information from data. See Baumeister and Hamilton (2015).

[6] Non-VAR approaches that assume a single unobservable unconventional monetary policy shock also include the event-study approach (Gagnon et al. 2011, Joyce et al. 2011, Krishnamurthy and Vissing-Jorgensen 2011, Swanson 2011, and Ueda 2012) and the difference-in-difference approach (Foley-Fisher, Ramcharan, and Edison 2016, and Rodnyansky and Darmouni 2017).

[7] As we discuss in Section 2.2, we use the BOJ's unconventional asset ratio to capture the qualitative easing shock and we include various financial assets from long-term government bonds to stocks as unconventional assets to calculate the ratio. However, purchasing different unconventional assets could have different effects on the economy. In this paper, we do not investigate each of the different effects because we focus on the entire effect of purchasing unconventional assets.

favorable effects on the macroeconomy. The identification of shocks, however, is unsuitable in terms of the actual dynamics of the unconventional and conventional policy indicators. More specifically, the size and composition of a central bank's balance sheet may not reflect the policy changes of the central bank immediately after an announcement, whereas the bank's policy rate does. As the BOJ clarifies in its statement, the target levels of unconventional policy instruments are basically achieved after several months or a year has passed from the BOJ's policy change announcement. Hence, agents in the economy can anticipate large changes in monetary policy indicators, including the monetary base, even in the long-run future. If, however, we impose an existing identification scheme in a VAR model such as a recursive restriction and a sign restriction and ignore the difference between those unconventional policy indicators and the short-term policy rate, we run the risk of misspecifying those anticipated changes as unanticipated shocks.

Premising that monetary policy shocks are mainly attributable to the actual movements of observable unconventional policy indicators, we identify two unconventional monetary policy shocks relating to the size and composition of the BOJ's balance sheet as anticipated shocks, or news shocks, that best presage their current and future paths.[8] We identify the unconventional shocks using the maximum forecast error variance (MFEV) approach from Francis et al. (2014), a method that builds on the work of Faust (1998) in the framework of monetary policy analysis. The MFEV approach identifies a shock such that its contribution to the forecast error variance of a time-series process is maximized over all horizons up to a finite truncation horizon, whereas Faust's approach maximizes the contribution at a predetermined finite horizon. The effective use of the MFEV approach to identify the unconventional shocks in the BOJ's balance sheet operations requires a long truncation horizon, because the monetary base and composition of assets in the BOJ's balance

[8] Milani and Treadwell (2012) tried to theoretically disentangle the anticipated and unanticipated components of policy shocks by constructing a New Keynesian model that incorporates news about future policy rates. Tsuruga and Wake (2019) find that a time lag between the decision and implementation of money-financed fiscal stimulus may cause a recession by using a New Keynesian dynamic stochastic general equilibrium (DSGE) model, indicating the importance of distinguishing between anticipated and unanticipated stimulus.

sheets change only gradually after the BOJ announced the policy change, as we discuss in Section 2.2 in more detail. Therefore, when employing the MFEV approach, we adopt the 36-month truncation horizon.[9]

Two features of the MFEV approach make it more agnostic and flexible than the existing approaches in identifying unconventional policy shock. First, the MFEV approach requires no assumptions on signs of responses of the central bank's two balance sheet instruments. Second, the approach isolates the primary driver of a time-series process as an anticipated shock and can be applied to any case in which the same dominant driving process exists (Francis et al. 2014). The MFEV approach is suitable for identifying the two unconventional monetary policy shocks, given that the BOJ implements the unconventional monetary policy by altering the expected future course of monetary policy actions, including the balance sheet operations in its statement (Okina and Shiratsuka 2004).

Finally, the endogeneity issue is one of the main difficulties for the identification of monetary policy shocks. We should note that a simple MFEV relies on the variance-covariance matrix of VAR residuals. However, using simple VAR residuals would suffer from the endogeneity problem. To overcome this problem, we follow the literature of the external instrument variable approach for a structural VAR (SVAR) model and combine it with the MFEV method. To our knowledge, this is the first paper to combine the MFEV approach with the external instrument variable method for the identification of an SVAR model. More precisely, following in the vein of the previous literature, we focus on the monetary policy meeting days as the timing when monetary policy shocks arise in the economy (Kuttner 2001; Cochrane and Piazzesi 2002; Gürkaynak, Sack,

[9]Weale and Wieladek (2016) and Zeev, Gunn, and Khan (2020) share the similar motivation with us in identifying their unconventional monetary policy shocks. In addition to the recursive restriction and the sign restriction approach, Weale and Wieladek (2016) also employed Faust's (1998) approach to analyze the U.K. and U.S. unconventional monetary policy. They identified the asset purchase announcement shock as the process that most robustly explained the forecast error variance of asset purchases, with a three-month delay. On the other hand, like us, Zeev, Gunn, and Khan (2020) employed the MFEV approach with a much longer truncation horizon. They identified the U.S. forward guidance shock regarding the future path of the short-term policy rate, with the 15-, 30-, or 45-month truncation horizon.

and Swanson 2005a, 2005b, 2007; Honda and Kuroki 2006; Campbell et al. 2012; Gertler and Karadi 2015; and Nakamura and Steinsson 2018). The BOJ decides its policy scheme at monetary policy meetings (previously, the meetings were held once or twice a month) and publicly states its policy decision just after each meeting. We exploit the idea that monetary policy shocks are reflected in the changes of asset prices just after the BOJ deploys its main communication tool, the public statement that it issues on the latest monetary policy meeting. In other words, we use the market responses to the BOJ's policy decision statements, that is, the monetary policy surprises in financial markets or the revised expectations of market participants embedded in financial asset valuations.[10] Such price revisions in the financial markets can be used to measure the extent to which monetary policy announcements surprise the markets. We thoroughly utilize this insight to identify the BOJ's monetary policy shocks. More concretely, as long as we correctly characterize the monetary policy surprises, we can use them as the instrumental variables of the reduced-form VAR innovations to identify the causal effects of the BOJ's monetary policy shocks on macroeconomic variables.[11]

The remainder of this paper is organized as follows. Section 2 constructs our monetary policy surprise measures and examines the movement of each policy indicator in response to the BOJ's monetary policy shocks. Section 3 discusses a method to identify quantitative and qualitative monetary policy shocks as anticipated shocks. Section 4 reports the estimation results for the unconventional monetary policy shocks. Section 5 explores the robustness of our empirical findings on unconventional monetary policy effects, along with several implications of the findings. Section 6 closes the paper with

[10]Through this paper, we use the term "agents' revisions of expectations" to refer to the monetary policy surprises, or the revised expectations of market participants embedded in financial asset valuations as factors correlated with monetary policy shocks, whereas some studies measured such expectation revisions either directly through survey forecasts or indirectly through models that are designed to approximate the expectation formation process (see, e.g., Coibion and Gorodnichenko 2012). We acknowledge an anonymous referee for suggesting this point.

[11]See Stock and Watson (2012, 2018) and Ramey (2016) for detailed surveys of this empirical strategy for identifying U.S. monetary policy shocks using monetary policy surprises, namely, changes in asset market prices on Federal Open Market Committee dates.

concluding comments. The appendix provides detailed definitions of the variables used in this paper and detailed discussions on the development of the monetary policy indicators and estimated monetary policy shocks.

2. Monetary Policy Surprises and the Movements of Monetary Policy Indicators in Response

As we discussed earlier in the Introduction, the fundamental issue to consider in identifying monetary policy shocks in relation to policy indicators is the timing of the central bank's policy decision announcement. After beginning this section with a discussion of the source from which monetary policy shocks originate, we examine the movements of monetary policy indicators in response to monetary policy shocks. In doing so, we demonstrate why it becomes necessary to apply our method of using the structural VAR approach to identify monetary policy shocks in relation to each of three policy indicators, one conventional and two unconventional. The conventional policy indicator is the uncollateralized overnight call rate, that is, the BOJ's targeted short-term policy rate. The unconventional policy indicators are the monetary base and the composition ratio of the BOJ's unconventional assets to its total assets. The unconventional assets include long-term JGBs, ETFs, stock, REITs, commercial papers, and corporate bonds. In this paper, we categorize all risky assets into one category as unconventional assets and use the risky asset ratio as a policy instrument variable. This is because the appropriate number of factors required for the explanation is estimated to be three. Therefore, increasing the number of instruments to more than three generates complexity but does not provide better understanding of the role of each policy tool. In addition, the BOJ categorizes its unconventional policies into two dimensions. For example, Governor Kuroda[12] mentioned that the

[12] More precisely, in the speech at the meeting held by the Yomiuri International Economic Society in Tokyo (April 12, 2013), he mentioned as follows: "That is, the central banks' purchases of government bonds and other assets from the markets have the effect of encouraging further declines in long-term interest rates and lowering risk premia of asset prices by absorbing risks. . . Thus, it is important to work on two aspects of monetary easing, both in terms of quantity and quality."

different purchasing programs have two aspects, namely quantity and quality easing.[13] Within the framework of the BOJ's unconventional monetary policy, the unconventional assets ratio is regarded as a qualitative policy indicator (Shiratsuka 2010 and Ueda 2012), while the monetary base, or the size of the BOJ's balance sheet, is regarded as a quantitative policy indicator.

Note that we use the sample period from April 1998 to January 2016 throughout this paper. We selected this sample period for two reasons: first, because the BOJ publishes detailed data on its asset composition from April 1998; second, because the transmission mechanism through control of the short-term rate may change when the policy rate turns negative after the BOJ introduces a negative interest policy in February 2016 (see, e.g., Eggertsson et al. 2019 and Abadi, Brunnermeier, and Koby 2022). Appendix A provides detailed definitions of the variables used in this paper.

2.1 Monetary Policy Surprises

The BOJ decides its policy scheme in a monetary policy meeting (MPM) held about twice per month and publicly states its policy decisions just after the meeting closes. We can assume, therefore, that the BOJ's monetary policy shocks are reflected in revisions in the expectations of agents in the asset markets. This empirical strategy helps us overcome identification problems that would arise with regard to endogenous responses of monetary policy if we simply treated innovations of monetary policy indicators as policy shocks in a monthly or quarterly VAR model. If we were to apply the innovations in such VAR models, the models would be contaminated by their endogenous responses to the underlying financial variables and other macroeconomic variables left out of the VAR system (Faust, Swanson, and Wright 2004; Romer and Romer 2004; Gertler and Karadi 2015; and Shibamoto 2016).[14] As an alternative, therefore,

[13]However, the detailed categorization and separate examination of each asset purchasing program could help us to understand the mechanism and effect more precisely. This will be our future research topic. We thank an anonymous referee for pointing out this important issue.

[14]Faust, Swanson, and Wright (2004), Romer and Romer (2004), Gertler and Karadi (2015), and Shibamoto (2016) pointed out that the reduced-form VAR

we use monetary policy surprises in asset markets, or revisions in the expectations of agents in asset markets, as external instruments to control for the endogenous responses of the three monetary policy indicators not only to the financial variables in the VAR but also to underlying correlated variables out of the VAR. This approach will be discussed in the next section.

Previous studies constructed monetary policy surprises by focusing on changes in short-term interest rate futures and using high-frequency daily trading data. Kuttner (2001), Cochrane and Piazzesi (2002), Gürkaynak, Sack, and Swanson (2005a, 2005b, 2007), Campbell et al. (2012), Gertler and Karadi (2015), and Nakamura and Steinsson (2018) constructed monetary policy surprises in federal funds or Eurodollar futures occurring on Federal Open Market Committee dates. Honda and Kuroki (2006) constructed monetary policy surprises in euro-yen futures occurring on the BOJ's MPM dates from 1989 to 2001. Although these studies examined financial market responses to exogenous monetary policy shocks under the conventional policy regime, this empirical strategy is still useful for identifying the BOJ's monetary policy shocks under the unconventional policy regime.

This strategy, however, is of limited use for our purposes, given that short-term interest rate futures have hardly changed since the BOJ introduced its unconventional monetary policy. Here, therefore, we depart from the previous studies by looking beyond changes in a particular asset market and exploiting all information on changes in the major financial markets just before and just after the BOJ's public statements. More concretely, we employ the principal component approach of Bernanke, Reinhart, and Sack (2004), Gürkaynak, Sack, and Swanson (2005a), and Swanson (2017) to prepare for monetary policy surprises as common factors of unanticipated changes in the major financial market variables following public statements. If we obtain l common factors for market participant surprises over a central bank's policy decisions, we can construct at most l types of monetary policy shocks.

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innovations of policy rates would have a substantial bias in identifying the monetary policy effect.

The principal component analysis of monetary policy on meeting day t is based on the following equation:

$$\mathbf{X_t} = \mathbf{\Lambda F_t} + \eta_\mathbf{t}, \tag{1}$$

where $\mathbf{X_t} = (x_{1t}, \ldots, x_{nt})'$ denotes the vector of n financial time series, $\eta_\mathbf{t}$ indicates the vector of n idiosyncratic disturbance terms, $\mathbf{F_t}$ is the vector of l unobserved common factors, and $\mathbf{\Lambda}$ is a matrix of the coefficients identified as factor loadings. We aim to extract common factors $\mathbf{F_t}$ by using the factor model. We include 12 financial market variables x_{it} $(i = 1, \ldots, 12)$: one futures rate (three-month euro-yen TIBOR futures), five yen interest swap rates (1, 2, 5, 10, 30 years), one short-term spot rate (three-month euro-yen TIBOR), two spot exchange rates on the Tokyo market (yen-U.S. dollar and yen-AUS dollar), two stock indices (TOPIX and Nikkei JASDAQ), and bank reserve deposits.[15]

Our inclusion of asset variables in calculating principal components is similar to that in Swanson (2021); that is, he exhaustively utilized the information on various types of asset prices, such as federal fund futures, Eurodollar futures, and Treasury bond yields. In addition, we include the stock market index and exchange rates in order to capture the BOJ's policy measures appropriately. More specifically, the BOJ started to purchase exchange-traded funds that track stock indices from 2010 and then expanded the purchasing amount. In 2021, it reaches about 5 percent of the total market value of all stocks listed in the first section of the Tokyo Stock Exchange. In addition, the BOJ has paid special attention to exchange rates, as Governor Kuroda pointed out in his speech.[16] To capture the

[15]In the baseline specification, we do not control for macroeconomic news about real economic activity or inflation in the dynamic factor model. Hence, our monetary policy surprises could include information on the macroeconomic news other than the monetary policy itself. Following an anonymous referee's suggestion, to control for macro news release on policy meeting days, we use the macroeconomic news shocks defined as the difference between an actual value (for the index of industrial production and the consumer price index) and its market forecasts from the Monetary Market Services (MMS) survey. We found that our results reported below do not change much qualitatively and quantitatively. We acknowledge the referee's suggestion.

[16]Governor Kuroda pointed out that one of the four major channels of monetary easing is "a channel through which the yen depreciate due mainly to an

distinct feature of the BOJ's monetary policy, we include the stock market index and exchange rates. This approach allows us to investigate what number of dimensions best describes monetary policy without selecting one particular asset price as a sufficient statistic for monetary policy, as in Gertler and Karadi (2015) and Nakamura and Steinsson (2018), who aimed at summarizing monetary policy with the one- or two-year Treasury yield.

We calculate the differences in the seven interest rate variables and the log differences of the two exchange rates, two stock indices, and bank reserves as percentages of the rate of change before and after public statements. More concretely, we use the closing values at 3:00 p.m. from the day before the public statement to the day after the statement to calculate changes of the 12 financial variables over the two-day period in order to duly consider the timing of the public statement and the time required for the news to be sufficiently recognized (see Ueda 2012).[17] That is, for stock prices, exchange rates, and bank reserves, x_{it} is defined as follows:

$$x_{it} = \log(P_{it+1}/P_{it-1}) \times 100, \tag{2}$$

and for interest rates,

$$x_{it} = r_{it+1} - r_{it-1}, \tag{3}$$

where P_{it+1} and P_{it-1} indicate the closing values of exchange rates, stock indices, and bank reserves on the day after a monetary policy meeting and the closing values of the same on the day before the monetary policy meeting, respectively, and r_{it+1} and r_{it-1} denote the closing interest rates.

We preliminarily exclude the dates of the meetings at which the BOJ coordinated policy with the Federal Reserve, the European

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expansion in yield differentials between Japan and other economies" in the speech at the Meeting of Councillors of Nippon Keidanren (Japan Business Federation) on December 23, 2021.

[17] An event-study analysis by Ueda (2012) showed that asset prices, including TOPIX and Japanese government bond yields, significantly respond to monetary policy changes from two days after the BOJ's public statements onward. For a robustness check, however, we also used narrower time windows to extract the monetary policy surprises. We found that the results are qualitatively the same as those reported below.

Table 1. The Number of Common Factors Underlying the Changes in Financial Market at the MPM

Number of Factors: *k*	**0**	**1**	**2**	**3**	**4**
$BN(k)$	2.98	2.94	3.06	2.89	2.95
$AH(k)$	n.a.	1.05	0.89	1.09	0.52

Note: $BN(k)$ denotes the Bai and Ng (2002) information criteria, defined as follows:

$$BN(k) = \log(V(k)) + k\left(\frac{n+T}{nT}\right) log\left(\frac{nT}{n+T}\right),$$

where n is the number of variables in factor model (1): $n = 12$. T is the number of observations. $V(k)$ is the sum of squared residuals divided by nT. $AH(k)$ denotes the Ahn and Horenstein (2013) information criteria, defined as follows:

$$AH(k) = \frac{\log(V(k-1))/\log(V(k))}{\log(V(k))/\log(V(k+1))}.$$

Central Bank, or the Bank of England. We also exclude the date on which the BOJ agreed on its policy responses to the Tohoku earthquake of March 11, 2011, as policy coordination and disaster response would be likely to contaminate the BOJ's policy effects.[18]

We select the number of common factors using the information criteria proposed by Bai and Ng (2002) and Ahn and Horenstein (2013): the former and the latter respectively suggested that the preferred model is the one that minimizes and maximizes the information criteria. Table 1 reports the two information criteria applied. These criteria suggest that we should adopt three common factors as monetary policy surprises in the 12 financial markets.[19]

[18]The BOJ held meetings on September 18, 2008, September 29, 2008, and November 30, 2011 to coordinate policy. In a meeting on March 14, 2011, the BOJ agreed on its policy response to the Tohoku earthquake.

[19]To examine the importance of including the stock market indices and exchange rates, we also conduct factor analysis by excluding them. If we exclude those variables, we would summarize monetary policy by just one dimension. However, this is implausible when we consider the fact that the BOJ implemented various unconventional policy measures in this period, as discussed in Swanson (2021) for the Federal Reserve's policy. In other words, we would miss other substantial dimensions of monetary policy that involve the stock price indices and exchange rates if we exclude them. We thank the anonymous referee for pointing out this important issue.

We can therefore construct at most three types of monetary policy shocks.

When constructing monthly data on the monetary policy surprises, we extract the common factors jointly over all the surprises and then use a sum within each month, as in Romer and Romer (2004) and Barakchian and Crowe (2013).

2.2 Monetary Policy Indicators' Response

In this subsection we examine the statistical relevance among the monetary policy surprises and monetary policy indicators based on how differently each of the monetary policy indicators responds to monetary policy shocks whose information is contained in monetary policy surprises. To this end, we run the following distributed lag regression of the policy indicators on the current and lagged monetary policy surprises:[20]

$$PI_t = \sum_{j=1}^{3} \sum_{h=0}^{H} r_h^j \; PS_{t-h}^j + \text{Controls} + e_t^{PI}, \tag{4}$$

where PI_t denotes the change or the level in each of the monetary policy indicators—the short-term policy interest rate (SR), monetary base (MB), and composition ratio of the BOJ's unconventional assets to total assets (COMP)—in month t. The change in the monetary base is expressed using the monthly growth rates (annual rate) of the log-differenced values. The level in the monetary base is expressed using logarithmic values × 1200. PS_{t-h}^j denotes the h lagged values for the three monetary policy surprises generated using the factor analysis. e_t^{PI} denotes stochastic disturbances. Controls include a constant term and the one-lagged value of PI_t.

Table 2 reports chi-square statistics and P-values for testing the null hypothesis, $r_h^j = 0$ for all $j = 1, 2, 3$, in the distributed lag regression at the horizon of $h = H$. As the table shows, the monetary policy surprises are statistically correlated with the monetary policy indicators but associate with the indicators in different ways. Specifically, we find that the monetary policy surprises are significantly associated with the short-term policy rate ($\Delta \mathrm{SR}_t$ and SR_t)

[20] This regression is essentially the same as the local projection method (see Jordà 2005 and Stock and Watson 2018).

Table 2. Results for the Distributed Lag Regression of Each Monetary Policy Indicator on Monetary Policy Surprises

	Change in Policy Indicator			Level in Policy Indicator		
	Δ MB	**Δ COMP**	**Δ SR**	**MB**	**COMP**	**SR**
$H = 0$	2.91	4.57	13.48	1.03	4.89	17.91
	[0.41]	[0.21]	[0.00]	[0.79]	[0.18]	[0.00]
$H = 1$	3.67	5.23	25.83	1.40	5.93	31.71
	[0.72]	[0.52]	[0.00]	[0.97]	[0.43]	[0.00]
$H = 2$	8.54	17.88	33.74	6.45	19.59	47.90
	[0.48]	[0.04]	[0.00]	[0.69]	[0.02]	[0.00]
$H = 6$	20.75	27.74	81.40	26.97	31.06	96.60
	[0.47]	[0.15]	[0.00]	[0.17]	[0.07]	[0.00]
$H = 12$	54.41	61.23	67.15	69.19	72.11	107.94
	[0.05]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
$H = 24$	126.97	527.22	288.39	171.72	470.89	394.72
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

Note: The distributed lag regression model is specified as Equation (4). This table shows chi-square statistics (p-values in brackets) resulting from tests of the null hypothesis: $r_h^j = 0$ for all $j = 1, 2, 3$ and $h = 0, \ldots, H$.

at the horizon of $H = 0$, or the contemporaneous time of the policy shock arrival. This association tells us that the short-term policy rate immediately responds to the BOJ's policy changes. In contrast, monetary policy surprises show no significant associations with the monetary base ($\Delta\mathrm{MB}_t$ and MB_t) or the unconventional assets ratio ($\Delta\mathrm{COMP}_t$ and COMP_t) at the horizon $H = 0$, but are significantly associated with the monetary base at $H \geq 12$ and with the unconventional assets ratio at $H \geq 2$. These estimation results imply that the monetary base and unconventional assets ratio respond to the BOJ's policy changes slowly and later in time.

Our finding on the responses of the quantitative and qualitative monetary policy indicators clearly indicates that monetary policy surprises have substantial information on their future movements, but not on their contemporaneous ones. In other words, the public statements issued just after the MPM on the bank's decision to change the two unconventional policy indicators behave like anticipated shocks that portend future changes in the indicators. Therefore, if we were to impose an existing identification scheme in a VAR model such as a recursive restriction and a sign restriction and ignore the difference between those unconventional policy indicators and the short-term policy rate, we would misspecify those anticipated changes as unanticipated shocks. In the next section we incorporate these medium- and long-term findings among the monetary policy surprises and two unconventional policy indicators into an identifying restriction on the intertemporal relations among the unconventional monetary policy shocks and indicators.

Note, also, that each of the monetary policy indicators associates differently with the monetary policy surprises. The differences between the associations compel us to separately identify the three monetary policy shocks relating to the three policy indicators: one conventional monetary policy shock that aims to exogenously change short-term nominal interest rates and two unconventional monetary policy shocks that aim to exogenously change the size and composition of the central bank's balance sheet.

3. Identifying Quantitative and Qualitative Monetary Policy Shocks

This section describes the empirical strategy we use to identify the effects of the two unconventional monetary policy shocks (quantitative and qualitative monetary policy shocks) and the one short-term policy rate shock with the three principal components of the monetary policy surprises in the structural VAR analysis. First, we assume that monetary policy shocks originate from the public statements released just after the MPM. Second, we account for the identifying restrictions that incorporate the features of the monetary policy indicators discussed in Section 2. Specifically, we impose restrictions on unconventional monetary policy shocks as shocks that capture current and future changes in the size and composition of the BOJ's balance sheet, and we define the short-term policy rate shock as a shock that is extracted after the unconventional monetary policy shocks. In Section 5 we show that estimated impulse responses to the quantitative and qualitative policy shocks based on this assumption are robust even under the alternative assumption that the policy rate shock is followed by the two unconventional policy shocks involving the central bank's balance sheet operations.

Also note that in setting the VAR model, we change our assumptions about the entry of a new policy scheme in an unconventional monetary policy regime. When, for example, the central bank introduces or halts a zero interest rate policy, quantitative easing policy, or quantitative and qualitative easing policy, we assume that the new scheme reflects not a change in the central bank's deep parameter in its policy decision announcement, but a policy shock that either portends future changes in the monetary base and unconventional assets ratio or leads to an immediate change in the short-term policy rate. Below, therefore, we make no use of regime-switching and time-varying parameter VAR models such as those of Fujiwara (2006), Kapetanios et al. (2012), Baumeister and Benati (2013), Kimura and Nakajima (2016), Miyao and Okimoto (2017), Hayashi and Koeda (2019), and Koeda (2019).

Our procedure for VAR identification is based on the following two-step approach. In the first step, we use the monetary policy surprises as the instrumental variables of the reduced-form VAR innovations of the three policy indicators and other macroeconomic variables. Specifically, we construct an impact matrix for the instantaneous responses of the VAR variables by disentangling the causal relationships among the monetary policy shocks and VAR variables. The impact matrix in this stage disregards the movement in the unconventional policy indicators following policy changes. We therefore impose restrictions, in the second step, to identify the quantitative and qualitative shocks, which we define as shocks that best explain the changes in the conditional expectation about the current and future paths of the size and composition of the central bank's balance sheet. To this end, as discussed in the Introduction, we employ the maximum forecast error variance (MFEV) approach from Francis et al. (2014).

3.1 Structural VAR Model

Letting y_t denote a $K \times 1$ vector of time-varying observables in month t, this stochastic structure can be expressed in terms of the vector moving average representation:

$$y_t = \Phi(L)u_t, \tag{5}$$

where $\Phi(L) = I + \Phi_1 L + \Phi_2 L^2 + \cdots$ is a matrix polynomial in the lag operator, L, and u_t denotes the $K \times 1$ vector of the reduced-form VAR innovations. The monetary base (MB), unconventional assets ratio (COMP), and short-term policy rate (SR) are given by the first, second, and third elements of y_t, respectively. The structural vector moving average representation can thus be written as follows:

$$y_t = \Psi(L)\epsilon_t, \tag{6}$$

where $\Psi(L) = \Psi_0 + \Psi_1 L + \Psi_2 L^2 + \cdots$, and ϵ_t denotes the $K \times 1$ vector of the structural shocks. Let ϵ_t^{MP} be the 3×1 policy shock vector $\epsilon_t^{MP} = [\epsilon_t^{QN}, \epsilon_t^{QL}, \epsilon_t^{SR}]'$, where ϵ_t^{QN}, ϵ_t^{QL}, and ϵ_t^{SR} denote unconventional quantitative, qualitative policy shocks, and conventional short-term interest rate shocks, respectively. The space spanned by the policy shock vector ϵ_t^{MP} is disentangled from the space spanned by other possible shocks of the $(K-3) \times 1$ vector ϵ_t^X in the following linear relation between the reduced-form VAR innovations u_t and structural shocks ϵ_t:

$$\begin{gathered} u_t = R\epsilon_t = R^{MP}\epsilon_t^{MP} + R^X \epsilon_t^X, \\ \underset{(K\times K)}{R} = [\underset{(K\times 3)}{R^{MP}}, \underset{(K\times(K-3))}{R^X}], \underset{(K+1)}{\epsilon_t} = [\underset{(3\times 1)}{\epsilon_t^{MP}}, \underset{((K-3)\times 1)}{\epsilon_t^X}]', \end{gathered} \tag{7}$$

where R^{MP} represents the impact matrix for the responses of the VAR variables y_t to the monetary policy shocks.

The variance-covariance matrix of the space spanned by the monetary policy shocks can be expressed as

$$\Sigma^{MP} = R^{MP} E(\epsilon_t^{MP} \epsilon_t^{MP'}) R^{MP'} = R^{MP} R^{MP'}, \tag{8}$$

where the variance of monetary policy shocks is normalized to one. The impact matrix R^{MP} satisfies the variance-covariance matrix but it is not unique. For some arbitrary orthogonalization of this impact matrix, $\tilde{R}^{MP}$, the entire space of possible impact matrices can be written as

$$R^{MP} = \tilde{R}^{MP} D, \tag{9}$$

where D denotes the 3×3 orthonormal matrix ($DD' = I$). Note that $\tilde{R}^{MP} d_j$ ($j = 1, 2, 3$) (where d_j is the 3×1 orthonormal vector indicating the jth column of the orthonormal matrix D) is the $K \times 1$ vector, and thus interprets the contemporaneous impact of the jth monetary policy shock on the VAR variables. In the following subsections we construct this impact matrix (9) to identify the three types of monetary policy shocks.

3.2 Controlling the Endogeneity of the Monetary Policy Indicators

We use three principal components of the monetary policy surprises (PS_t) extracted from the changes in the 12 major financial markets on MPM days as instrumental variables for the reduced-form VAR innovations, u_t. Thus, we aim to control for the endogeneity of the monetary policy indicators and disentangle the causal effects of the policy shocks on the VAR variables at the shock arrival time. More concretely, we conduct the following system regression:

$$u_t = \underset{(K \times 3)(3 \times 1)}{R^{PS} PS_t} + e_t, \tag{10}$$

where PS_t denotes the 3×1 vector of the three monetary policy surprises at a monthly frequency. The system regression yields the instantaneous responses of the VAR variables to the BOJ's public statements in the form of fitted values $u_t^{ps} = \hat{R}^{PS} PS_t$. We then obtain the following variance-covariance matrix incorporating the instantaneous impacts of the public statements on the VAR variables:

$$\Sigma^{PS} = E(u_t^{ps} u_t^{ps'}). \tag{11}$$

A diagonal element of this variance-covariance matrix, $\Sigma_{i,i}^{PS}$ ($i = 1, \cdots, k$), includes the instantaneous forecast error variances of the VAR variables attributable to the BOJ's public statements on MPM days.[21]

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[21]We find that the VAR innovations of the monetary policy indicators differently load on a linear combination of the three principal components through system regression (10) as shown in Table 3. For more details, see Section 4.1.

3.3 Identifying Quantitative and Qualitative Monetary Policy Shocks

Here we describe the second-step procedure to identify the conventional and unconventional monetary policy shocks. We identify the unconventional monetary policy shocks with help from the monetary base and unconventional assets ratio, assuming that agents believe that the policy indicators will meet their target levels after the BOJ's public statements on MPM days. To incorporate this feature into our identification of the unconventional monetary policy shocks, we define them as anticipated shocks that best portend the current and future paths of the monetary base and unconventional assets ratio.

This identification strategy requires that we model changes in the expectations regarding the current and future paths of the unconventional policy indicators. We do so by employing the MFEV approach proposed by Francis et al. (2014).[22] In this approach, we specify the changes in the conditional expectation based on a VAR model as maximization problems for the contributions of the unconventional policy shocks to the h-step-ahead forecast error variances of the unconventional policy indicators.

To explain the MFEV approach, we begin by expressing the h-step-ahead forecast error conditioning on the structural shocks ϵ_t:

$$y_{t+h} - E_{t-1}y_{t+h} = \sum_{\tau=0}^{h} \Phi_\tau R \epsilon_{t+h-\tau} = \sum_{\tau=0}^{h} \Phi_\tau R^{MP} \epsilon_{t+h-\tau}^{MP} + \sum_{\tau=0}^{h} \Phi_\tau R^{X} \epsilon_{t+h-\tau}^{X}, \tag{12}$$

where the first and second equalities use Equations (5) and (7). The h-step-ahead forecast error due to monetary policy shocks $\epsilon_{t+\tau}^{MP}$ can therefore be expressed as

[22] Barsky and Sims (2011) employed the MFEV approach to identify anticipated shocks related to future technology. Zeev, Gunn, and Khan (2019) used this approach to identify anticipated monetary policy shocks in the U.S. conventional monetary policy regime.

$$\sum_{\tau=0}^{h} \Phi_\tau R^{MP} \epsilon_{t+h-\tau}^{MP} = \sum_{\tau=0}^{h} \Phi_\tau \tilde{R}^{MP} D \epsilon_{t+h-\tau}^{MP}, \tag{13}$$

where the equality uses Equation (9). If we have orthogonalization matrix $\tilde{R}^{MP}$ and orthonormal vector d_j $(j = 1, 2, 3)$, we can therefore generate the impulse responses of the VAR variables to the jth monetary policy shock from the impact vector $\tilde{R}^{MP} d_j$.

We first prepare for an orthogonalization matrix $\tilde{R}^{MP}$ such that it satisfies the following condition:

$$\Sigma^{PS} = \tilde{R}^{MP} D D' \tilde{R}^{MP'}. \tag{14}$$

This equality ensures that the impact matrix $\tilde{R}^{MP} D$ is determined based on the estimated instantaneous responses $\hat{R}^{PS}$ of the reduced-form VAR innovations to the central bank's public statements in Equations (10) and (11). Next, we employ the MFEV approach, thereby obtaining the orthonormal vector d_j $(j = 1, 2, 3)$ with a given orthogonalization matrix $\tilde{R}^{MP}$ satisfying Equation (14), as discussed below.

From the h-step-ahead forecast error (13), the share of the h-step-ahead forecast error variance (FEV) of the unconventional policy indicator i $(i = 1, 2)$ attributable to the associated unconventional monetary shock $\epsilon_{j,t}^{MP}$ $(j = i)$ is expressed as a variance decomposition of the following form:

$$\Omega_j^i(h) = \frac{\iota_{1i}' \left(\sum_{\tau=0}^{h} \Phi_\tau \tilde{R}^{MP} D \iota_{2j} \iota_{2j}' D' \tilde{R}^{MP'} \Phi_\tau' \right) \iota_{1i}}{\iota_{1i}' \left(\sum_{\tau=0}^{h} \Phi_\tau \Sigma^{PS} \Phi_\tau' \right) \iota_{1i}}$$

$$= \frac{\overbrace{\sum_{\tau=0}^{h} \Phi_{i,\tau} \tilde{R}^{MP} d_j d_j' \tilde{R}^{MP'} \Phi_{i,\tau}'}^{\text{FEV of policy indicator } i \text{ due to } \epsilon_{j,t}^{MP}}}{\underbrace{\sum_{\tau=0}^{h} \Phi_{i,\tau} \Sigma^{PS} \Phi_{i,\tau}'}_{\text{FEV of indicator } i \text{ due to public statements}}}, \tag{15}$$

where i $(i = 1, 2)$ indicates the place of the unconventional monetary policy indicators (MB and COMP) in vector variable y_t, and j

$(j = i)$ indicates the place of the associated unconventional policy shocks ϵ_t^{QN}, ϵ_t^{QL}, and ϵ_t^{SR} in policy shock vector ϵ_t^{MP}. ι_{1i} and ι_{2j} are the $K \times 1$ and 3×1 selection vectors, with ones in the ith place and jth place and zeros elsewhere, and d_j is the 3×1 orthonormal vector indicating the jth column of the orthonormal matrix D. The selection vectors outside of the parentheses in both the numerator and denominator ι_{1i} pick out the ith row of the matrix of the moving average coefficients, which is denoted by $\Phi_{i,\tau}$.

Variance decomposition (15) models the extent to which the changes in expectations about the h-step-ahead path of unconventional policy indicator i at the time of the BOJ's public statement (represented by the denominator) are attributed to the associated unconventional policy shock j, denoted by $\epsilon_{j,t}^{MP}$ (where the contributed component of j is represented by the numerator). The MFEV approach to identify unconventional monetary policy shocks (i.e., quantitative and qualitative policy shocks) maximizes the variance decomposition by mapping unconventional policy indicator i to the associated unconventional policy shock j. This identification is based on the legitimate assumption that when the central bank announces its plans of action on two unconventional policy instruments—the change in the size of its balance sheet (MB) and the purchase of more or less unconventional assets (COMP)—agents will hear the announcement and update their expectations about the paths of the policy instruments accordingly. In other words, as long as the central bank keeps the its promises (at least for operations on the size of its balance sheet and the composition of its assets) and secures the agents' trust in the central bank's announcement, the identification of the associated two unconventional policy shocks based on the MFEV approach allows us to reveal the actual movements in the two balance sheet instruments after the unconventional policy shocks arrive.

Also note that unlike an existing identification scheme such as a recursive restriction or a sign restriction, the MFEV approach makes no assumption on how the size and composition of the central bank's balance sheet will respond after the bank makes a policy decision. This approach only assumes that agents revise their expectations of the path of a policy indicator according to the scheduling actions that the central bank announces with regard to the indicator. In this sense, the MFEV approach is more agnostic and flexible than the existing identification approach in identifying a particular type of policy shock relating to monetary policy indicators. Given the specific movements of the quantitative and qualitative policy measures following policy changes (see Subsection 2.2), this approach allows us to prevent misspecification of the quantitative and qualitative monetary policy shocks.

To identify the quantitative, qualitative, and short-term policy rate shocks with the MFEV approach, we begin by identifying the quantitative monetary policy shock, ϵ_t^{QN}, satisfying the following conditions:

$$\hat{d}_1 = \arg\max_{d_1} \; \Omega_1^1(h), \tag{16}$$

s.t.

$$d_1^{'} d_1 = 1. \tag{17}$$

Constraint (17) (d_1 have unit length) ensures that d_1 is the first column vector belonging to orthonormal matrix D. After obtaining $\hat{d}_1$ by solving the above maximization problem, we calculate the impulse responses of the VAR variables to the quantitative monetary policy shocks using the estimated impact vector $\tilde{R}^{MP}\hat{d}_1$.

Next, we identify the qualitative and conventional monetary policy shocks. Specifically, we identify the qualitative monetary shocks ϵ_t^{QL} by solving the following maximization problem:

$$\hat{d}_2 = \arg\max_{d_2} \Omega_2^2(h), \tag{18}$$

s.t.

$$d_2^{'} d_2 = 1, \tag{19}$$

$$d_2^{'} d_1 = 0, \tag{20}$$

$$d_1 = \hat{d}_1. \tag{21}$$

Constraints (19) and (20) ensure that d_2 is the second column vector belonging to orthonormal matrix D. Constraint (21) ensures that the qualitative shock is extracted after the quantitative shock. This implies that, in a qualitative shock with a target level for the monetary base given, the central bank aims to change the composition of its assets through, for example, an operation twist.[23] We can compute the impulse responses to the qualitative monetary policy shocks using the estimated impact vector $\tilde{R}^{MP}\hat{d}_2$.

Once two column vectors in the 3×3 orthonormal matrix D are given as its first and second column vectors $\hat{d}_1$ and $\hat{d}_2$, the third column vector d_3 is automatically determined. In the identification of the conventional short-term policy rate shock ϵ_t^{SR}, the third column in the impact matrix R^{MP} representing the impulse responses to the conventional policy rate shock is obtained as $\tilde{R}^{MP}\hat{d}_3$. The column vector is orthogonal to the first and second columns obtained through the above maximization problems, hence the surprise component of the monetary policy explains the small variation in the monetary base and unconventional assets ratio in the middle- and long-term period. In this sense, our identification strategy assumes that the central bank controls the short-term policy rate after it determined a plan of balance sheet extension and unconventional asset purchases. Section 5 demonstrated that even when we employ the alternative identification strategy in which a policy rate setting is assumed to precede a balance sheet setting, the estimated quantitative and qualitative policy effects do not depend on those identification strategies.

4. Results for Quantitative and Qualitative Monetary Policy Shocks

In this section we discuss the empirical results obtained using the monetary policy shocks identified by the method presented in the previous section. We focus on two unconventional monetary policy shocks, that is, quantitative and qualitative monetary policy shocks, in particular. In the VAR model, we include the monetary base (MB), unconventional assets ratio (COMP) as a percentage of total

[23] In the quantitative and qualitative monetary easing from March 2013, the BOJ targets a yearly expansion of the monetary base by 60 to 70 trillion yen (80 trillion yen from October 2014). To meet this monetary base target, the BOJ purchases exchange trade funds, commercial papers, and long-term government bonds. Given the fact that the BOJ sets the target level for the monetary base first, the recursive restriction for the quantitative and qualitative shocks is plausible.

assets, and short-term policy rate (SR) in basis points. For illustrative purposes, we multiply the logarithm of the monetary base by 1,200. Additionally, we include five macroeconomic variables in constructing the VAR: two asset market prices, two real economic variables, and one price indicator. The two asset market prices are the logarithm of the stock price index (SP) multiplied by 100 and the 10-year government bond yield (10YJGB) in basis points. The two real economic variables are the GDP gap (GGAP) in percentage points and the difference between the risky assets and safe assets held by commercial banks (BRISK) in trillion yen.[24] The risky asset holdings of commercial banks consist of equity holdings and bank lending, while the safe assets consist of JGBs. The consumer price index (CPI) is included as the price indicator. We also take the logarithm of CPI and multiply it by 1,200. See Appendix A for more detailed information on those variables in the VAR. As discussed in Section 2, our sample period is from April 1998 to January 2016. The number of lags in the VAR is determined to be two based on the Schwarz-Bayesian information criterion.

4.1 VAR Innovations and Monetary Policy Surprises

In what follows, we report the statistical relevance between the reduced-form VAR innovations and monetary policy surprises. Table 3 shows the estimation results for the system regression of the reduced-form VAR innovations on the three monetary policy surprises as expressed in (10).

The monetary policy surprises significantly explain only the reduced-form VAR innovations of the short-term policy rate (SR) and the asset prices (SP and 10YJGB), which tells us that the three asset price variables quickly respond to exogenous policy changes. On the contrary, the monetary policy surprises explain little of the unconventional policy indicators (MB and COMP), real economic variables (GGAP and BRISK), or price indicator (CPI) when the shock arrives. We know, therefore, that these latter variables show no immediate responses to the monetary policy shocks. In particular, the significant explanatory power of the short-term policy rate and

[24] We also use the unemployment rate, shipment of investment goods, and industrial production index in place of the GDP gap, but the results provided by these alternatives do not differ from the results reported below.

Table 3. Results for the Regression of Each VAR Innovation on Monetary Policy Surprises

	VAR Innovation: u_t							
	MB	**COMP**	**SR**	**SP**	**10YJGB**	**BRISK**	**GGAP**	**CPI**
PS^1	–2.68†	–0.19	–0.95**	0.03	–4.79**	–0.05	–0.01	0.04
	(1.62)	(0.22)	(0.35)	(0.49)	(1.71)	(0.27)	(0.01)	(0.19)
PS^2	–1.34	–0.27	0.96*	–3.85**	–0.93	–0.47	0.01	0.16
	(2.20)	(0.29)	(0.38)	(0.82)	(1.40)	(0.43)	(0.02)	(0.21)
PS^3	–1.02	–0.37	1.50*	2.16**	0.47	0.40	0.02	0.18
	(3.88)	(0.48)	(0.75)	(0.83)	(2.56)	(0.64)	(0.02)	(0.30)
χ^2	3.38	1.69	11.54	29.87	10.98	1.96	3.09	1.03
	[0.34]	[0.64]	[0.01]	[0.00]	[0.01]	[0.58]	[0.38]	[0.79]

Note: The regression model is specified as Equation (10). Values in parentheses are robust standard errors. **, *, and † indicate significance at the 1, 5, and 10 percent levels, respectively. χ^2 indicates chi-square statistics (p-values in brackets) resulting from tests of the null hypothesis that estimated coefficients on the three monetary policy surprises, PS^1, PS^2, and PS^3, are jointly zero for each VAR innovation u_t.

the weaker explanatory power of the quantitative and qualitative policy indicators are consistent with the results of the distributed lag regression (4) (see Subsection 2.2).

From these estimation results, we can interpret the three principal components in line with previous studies that extracted a principal component (Gürkaynak, Sack, and Swanson 2005a and Swanson 2017) or emphasized the informational effect of monetary policy (Campbell et al. 2012, Jarociński and Karadi 2020, and Andrade and Ferroni 2021). For example, PS^1 summarizes the policy surprises that involve the effect of monetary policy on the yield curve, like the longer-term policy factor of Gürkaynak, Sack, and Swanson (2005) and Swanson (2017) and the Odyssean forward guidance of Campbell et al. (2012) and Andrade and Ferroni (2021), which publicly commit the central bank to a long-term future action. On the other hand, PS^2 summarizes the policy surprises embodying the conventional effect that causes a negative association between the short-term policy rate and the stock price index, as discussed in Jarociński and Karadi (2020). By contrast, PS^3 indicates the policy surprises that involve the positive correlation between the short-term policy rate and the stock price index, like the informational shock of Jarociński and Karadi (2020) and the Delphic

Table 4. Forecast Error Variance Decomposition of Monetary Policy Indicators

Policy Indicator →	**Monetary Base**			**Composition**			**Short-Term Rate**		
Policy Shock →	***QN***	***QL***	***SR***	***QN***	***QL***	***SR***	***QN***	***QL***	***SR***
$h = 0$	0.83	0.17	99.00	9.60	16.34	74.06	36.22	53.29	10.49
$h = 12$	88.03	1.87	10.10	11.01	81.54	7.45	63.54	16.08	20.38
$h = 24$	94.68	2.97	2.36	28.87	65.36	5.77	54.64	27.88	17.47
$h = 36$	97.20	1.67	1.13	40.16	54.83	5.01	53.00	30.00	17.00
$h = 48$	97.70	1.66	0.64	48.06	47.67	4.27	51.97	31.36	16.67

Note: This table shows the estimated percentage share of the forecast error variance of each monetary policy indicator attributable to each monetary policy shock for h months ahead.

forward guidance of Campbell et al. (2012) and Andrade and Ferroni (2021), which presage near-future economic performance and likely subsequent policy actions.

4.2 Variance Decomposition Analysis

Table 4 presents the variance decomposition of the three monetary policy indicators attributable to each of the monetary policy shocks for $h = 0$, 12, 24, 36, and 48 months ahead, which is computed using Equation (15) for the MFEV approach.

While most of the variance of the monetary base (MB) and unconventional assets ratio (COMP) at $h = 0$ is attributable to the conventional policy rate shock, the table clearly shows that most of the variance of the two unconventional policy indicators at $h \geq 12$ is explained by their corresponding monetary policy shocks. More concretely, at $h \geq 12$ the quantitative shock explains almost all of the variance of the monetary base and the qualitative explains almost all of the variance of the unconventional assets ratio, while at $h \geq 36$ the two types of shock explain the variance of the unconventional assets ratio equally. This implies that the extension of the BOJ's balance sheet is realized slowly and gradually and that its medium- and long-term purchasing of unconventional assets is determined in accordance with the balance sheet extension.

The quantitative and qualitative monetary policy shocks appear to explain most of the variance of the short-term policy rate (SR).

The variance of the policy rate at $h = 0$ is almost fully attributable to the qualitative policy shock, but most of the variance at $h \geq 12$ is accounted for by the quantitative policy shock. Our finding that the short-term policy rate shock accounts for much rather than little of the variance is consistent with the identifying assumption that the central bank's planning balance sheet operations dictates its control of the short-term policy rate. In Subsection 5.1, we will discuss a case in which the central bank's policy rate control comes before the balance sheet size and composition are controlled.

4.3 Impulse Response Analysis

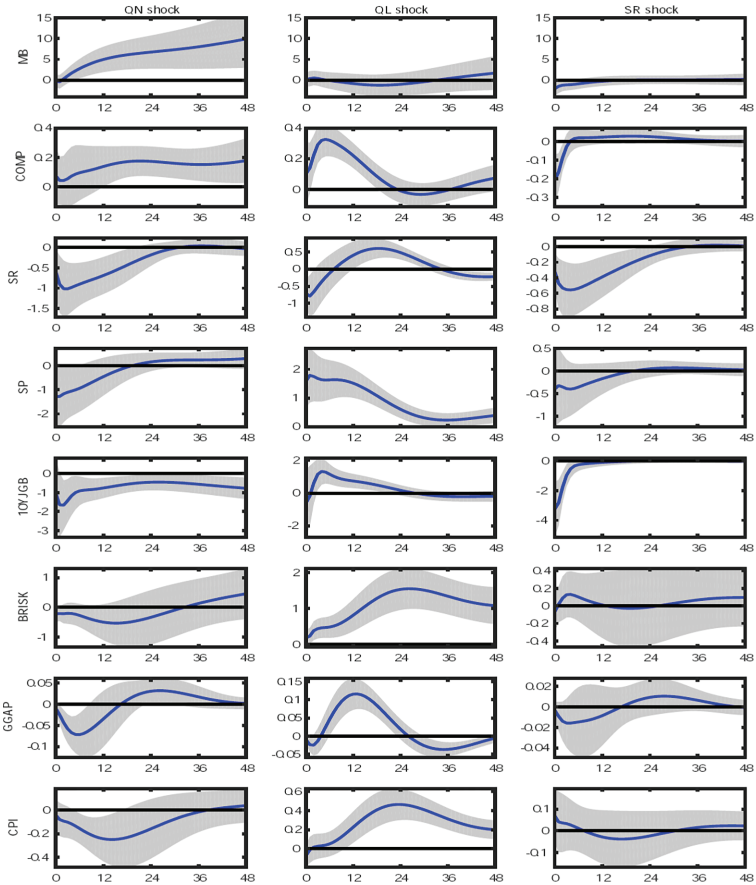
In this subsection we describe the estimated impulse responses to the exogenous monetary policy shocks. Figure 2 outlines the estimated impulse responses to the quantitative policy shock, the qualitative policy shock, and the short-term policy rate shock.[25]

4.3.1 Effects of Quantitative Shocks

As the left column of Figure 2 shows, the quantitative easing shock leads to a gradual and continuous increase in the monetary base (MB) without affecting it immediately. The monetary base reaches a peak at around one year following the quantitative easing shock. We can thus identify the quantitative shock as an anticipated shock linked to the expansion of the balance sheet (i.e., agents expect the monetary base to reach its target level soon after the BOJ announces its new target). The quantitative easing shock also leads to a slow increase in the unconventional assets ratio (COMP), which

[25] We employ a parametric bootstrap to compute the confidence intervals in the following; we randomly replace the pair of the three common factors and the VAR residuals, and then generate a bootstrap sample of each macroeconomic variable by substituting the resampled VAR residuals into the estimated VAR model. After obtaining VAR residuals by reestimating the VAR model with the bootstrap sample of macroeconomic variables, we use the reestimated VAR residuals and the resampled common factors to calculate impulse responses to the monetary policy shocks through Equations (10)–(21). We repeat this procedure 1,000 times to compute one standard error confidence band. Following Jentsch and Lunsford (2016), we also use the moving-block resampling to compute confidence intervals for robustness check. Confidence intervals based on the moving-block resampling with the block length of 12 is not so different from those based on our simple bootstrap resampling with the block length of 1.

Figure 2. Impulse Responses to the Quantitative Easing, Qualitative Easing, and Short Rate Shocks



Note: See Section 3 for details on the identification of each of the monetary policy shocks. The solid lines represent the point estimates of the impulse responses to a monetary policy shock in the eight-variable VAR model. The shaded areas represent the ± one-standard-error confidence band calculated by the bootstrap method with 1,000 replications. The bootstrap with external instruments involves resampling from the instruments. The impulse response functions (IRFs) of the short-term policy rate (SR) and the 10-year yield (10YJGB) are reported in basis points, while the IRFs of commercial bank holdings of risky assets (BRISK) are reported in trillion yen. The IRFs of the other variables are reported in percentage points.

clearly shows that the BOJ tends to increase its unconventional assets more than its conventional assets when expanding its balance sheet.

In estimating the responses of the nominal interest rates, we find that the short-term policy rate (SR) and long-term nominal interest rate (10YJGB) both fall immediately, but that the latter falls more. The immediate response of the long-term interest rate implies that a quantitative easing shock has a policy duration effect that decreases long-term interest rates immediately by working as a signal about the future path of policy rates.

The quantitative easing shock confers no favorable effects on the stock price (SP) or the commercial bank holdings of risky assets (BRISK), so both of the variables decline. We can infer, from the estimation results, that the quantitative easing shock was in no way effective in bringing about a portfolio rebalance where financial institutions with safer assets could be expected to lend more and increase the purchase of relatively risky assets, including stocks. Rather, the quantitative easing shock appeared to merely result in a tight supply/demand balance in the long-term Japanese government bond market or to change the market's expectations on the duration of the zero interest rate policy (Okina and Shiratsuka 2004 and Ugai 2007).

Consistent with this inference, the quantitative easing shock brought about less than favorable effects on the GDP gap (GGAP) and price indicator (CPI), as well.[26] Given that this shock significantly decreases the long-term nominal interest rate and generates a flattening yield curve, we can infer that the interest rate channel through the decrease in the long-term nominal interest rate in response to quantitative easing fails to bring about the intended effects under Japan's unconventional monetary policy regime.

4.3.2 Effects of Qualitative Shocks

As we see in the middle column of Figure 2, the qualitative easing shock has a significant effect on the unconventional assets ratio (COMP) without imparting a contemporaneous impact. More concretely, the unconventional assets ratio peaks almost six months later. On the contrary, the monetary base (MB) shows no significant response to the qualitative easing shock.

[26] Hayashi and Koeda (2019) found that exiting from the quantitative easing policy is expansionary if the actual-to-required reserve ratio is not unduly large.

In contrast to the quantitative easing shock, the qualitative easing shock leads to a substantive increase in the stock price (SP), an increase in the long-term nominal interest rate (10YJGB), and a persistent increase in the commercial bank holdings of risky assets (BRISK). Unlike the effects we find when the BOJ expands its balance sheet, the larger purchases of unconventional assets under the qualitative easing policy increase the stock price and generated a steepening yield curve. Qualitative easing also prompts financial institutions to increase the purchase of unconventional assets and lend more in portfolio rebalancing.

For the estimated responses of the other real economic variables, the GDP gap (GGAP) and price indicator (CPI) both increase significantly.

4.3.3 Policy Rate Shock Effects under Planning the Balance Sheet Structure

As the right column of Figure 2 shows, a short-term policy rate shock that significantly decreases the policy rate leads not to a change in the monetary base (MB), but to an immediate decrease in the unconventional assets ratio (COMP). This effect tells us, as discussed in Section 3, that our identification scheme assumes that the BOJ determines its evolution of balance sheet structure before an actual change in the short-term policy rate. Once the BOJ decides to decrease (increase) the policy rate, however, the central bank implements the policy rate control temporarily by purchasing (selling) conventional assets and selling (purchasing) unconventional assets and by increasing the prices of conventional (unconventional) assets, with the balance sheet size unchanged.

In such identification of the short-term policy rate shock, the long-term nominal interest rate (10YJGB) immediately and substantially falls and the yield curve temporarily flattens. By contrast, the stock price (SP), the commercial bank holdings of risky assets (BRISK), the GDP gap (GGAP), and the price indicator (CPI) do not significantly respond to the short-term policy rate shock when the balance sheet is of a given size. These neutral effects of the policy rate shock on the stock price and real economy differ from those demonstrated in the VAR literature for conventional monetary policy effects.[27] This difference suggests that if the central bank keeps the size of its balance sheet unchanged in controlling the short-term policy rate (as seen in the normalization of the U.S. monetary policy since December 2015), the stock price and real economy could be neutral to the policy rate change.

In Section 5, we extend our impulse response analysis by conducting a robustness check based on the alternative identification scheme in which the central bank sets its policy rate before it sets its balance sheet structure.

5. Unconventional Monetary Policy Effects and Robustness

In this section we conduct a robustness check based on an alternative identification strategy in which the central bank is assumed to control the short-term policy rate before it plans its balance sheet structure. We also explore several implications of the unconventional monetary policy effects on the macroeconomy by focusing on comparisons with the existing VAR studies and hypotheses to be further investigated on the topic of unconventional policy effects.

5.1 Alternative Identification and Robustness

To conduct a robustness check based on the alternative identification strategy, we introduce two additional identifying constraints besides constraints (16) to (21):

$$\tilde{r}_{31}d_{1,1} + \tilde{r}_{32}d_{2,1} + \tilde{r}_{33}d_{3,1} = 0, \tag{22}$$

and

$$\tilde{r}_{31}d_{1,2} + \tilde{r}_{32}d_{2,2} + \tilde{r}_{33}d_{3,2} = 0, \tag{23}$$

where $\tilde{r}_{31}$, $\tilde{r}_{32}$, and $\tilde{r}_{33}$ indicate the element of the third-row vector of $\tilde{R}^{MP}$ related to the policy rate response to monetary policy shocks.

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[27]See, e.g., Bernanke and Blinder (1992), Christiano, Eichenbaum, and Evans (1996), and Bernanke and Mihov (1998) for details on the U.S. conventional monetary policy. See, e.g., Miyao (2000, 2002), Nakashima (2006), and Shibamoto (2016) for details on the Japanese conventional monetary policy.

The two constraints ensure that the central bank controls its policy rate before it controls its evolution of balance sheet. Put differently, the quantitative and qualitative monetary policy shocks have no immediate impacts on the short-term policy rate.[28] Figure 3 reports estimated impulse responses to the quantitative, qualitative, and short-term policy rate shocks based on this alternative identifying scheme.

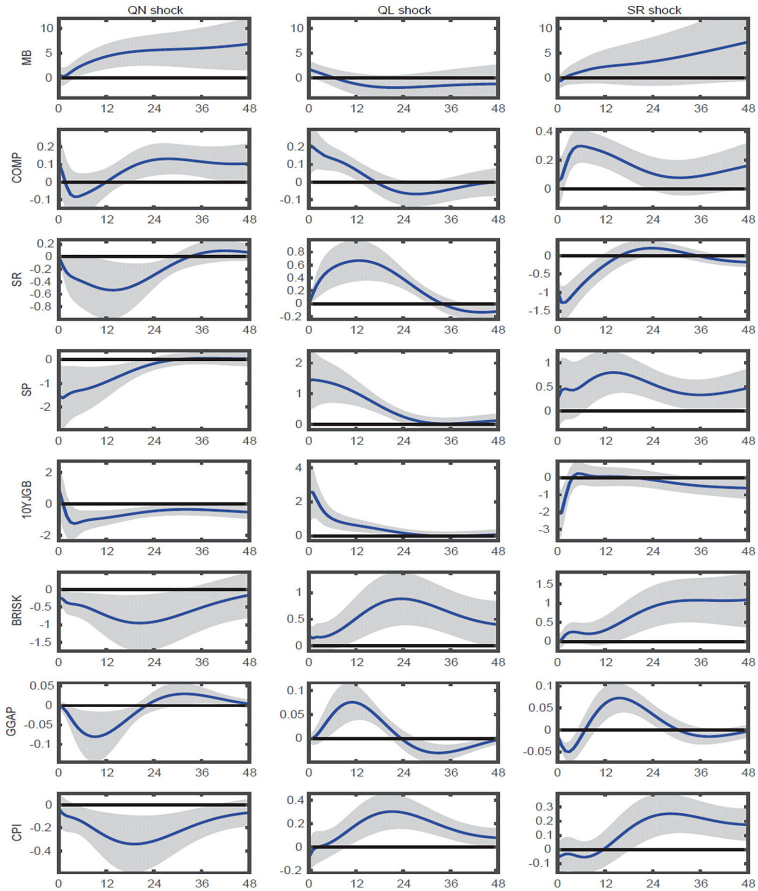
The left and middle columns of Figure 3 clearly show that although the quantitative and qualitative easing shocks reflect no instantaneous response of the short-term policy rate in accordance with the predetermined policy rate assumption, the unconventional policy easing shocks generate the same patterns of impulse responses as those based on the predetermined balance sheet assumption (see Subsection 4.3). In this sense, our unconventional policy effects are robust irrespective of those different identifying schemes.

Unlike the policy rate shock under planning balance sheet operations, under the assumption that the BOJ sets policy rate before determining the balance sheet size and composition, the policy rate shock basically produces impulse responses similar to those demonstrated in the VAR literature for conventional monetary policy effects (see the right column of Figure 3). In this sense, the policy rate control that comes before the balance sheet setting can be seen as the conventional monetary policy even in an extremely low interest regime, while the policy rate control subject to the long-term balance sheet control can be seen as an unconventional policy option in the central bank's balance sheet operations.

This contrast between the two types of short-term policy rate shocks can also be observed in their different results for the variance decomposition of the three monetary policy indicators. Table 5 reports results for the variance decomposition attributable to the associated monetary policy shocks. Compared with the policy rate control subject to the balance sheet control (see Subsection 4.2),

[28] More precisely, once the policy rate shock is determined before the quantitative and qualitative policy shocks under identifying restrictions (22) and (23) and the quantitative shock is determined before the qualitative shock by solving maximization problem (16) and obtaining $\hat{d}_1$, the qualitative shock is automatically determined without solving maximization problem (21). As far as this identification strategy in maintained, however, such automatic determination of the qualitative shock is formally equivalent to solving maximization problem (21).

Figure 3. Impulse Responses to the Monetary Policy Shocks under Alternative Identification



Note: Subsection 5.1 discusses the details of identification of the monetary policy shocks. Also see the note to Figure 2.

the assumption that the BOJ sets the policy rate prior to setting other policy tools generates the estimation result showing substantive increases in the contribution of the short-term policy rate shock to the variance of each of the policy indicators.

In this type of identification of the policy rate shock, Figure 3 shows that the policy easing that immediately decreases the

Table 5. Forecast Error Variance Decomposition of Monetary Policy Indicators under Alternative Identification

Policy Indicator →	**Monetary Base**			**Composition**			**Short-Term Rate**		
Policy Shock →	***QN***	***QL***	***SR***	***QN***	***QL***	***SR***	***QN***	***QL***	***SR***
$h = 0$	0.25	98.63	1.11	47.54	21.78	30.68	0	0	100
$h = 12$	57.76	5.39	36.85	34.51	18.63	46.86	42.84	3.68	53.48
$h = 24$	66.76	1.66	31.58	39.33	14.76	45.94	56.87	3.80	39.34
$h = 36$	71.36	1.18	27.46	50.64	11.52	37.84	53.81	9.51	36.68
$h = 48$	74.15	1.22	24.63	56.19	10.17	33.65	46.12	18.85	35.04

Note: This table shows the estimated percentage share of the forecast error variance of each monetary policy indicator attributable to each monetary policy shock for h months ahead.

short-term policy rate (SR) leads to an increase in both the monetary base (MB) and unconventional assets ratio (COMP). The estimated impulse responses of the stock price (SP) remain less than significant for about one year after the policy rate shock, then increase steadily from the end of the first year to the end of the third year. The long-term nominal interest rate (10YJGB) immediately decreases and the long-short spread narrows, responding to the policy rate shock. From the positive responses of the commercial bank holdings of risky assets (BRISK), we can infer that the policy easing shock causes a portfolio rebalance. The policy rate shock leads to increases in both the GDP gap (GGAP) and price indicator (CPI), though the former initially decreases in the first few periods. The GDP gap peaks after the price indicator begins to increase, at about the one-year point after the policy rate shock.

5.2 Comparison with Unanticipated Policy Shocks

As discussed in the Introduction, a number of previous studies have assumed that monetary aggregates such as the monetary base and excess reserves represent the central bank's policy stance. These studies have thus employed the standard recursive VAR approach or extensions of that approach, such as regime-switching or time-varying parameter VAR models. Another VAR approach employed in previous studies assumes that unconventional monetary policy shocks can be represented collectively as a single unobservable policy shock. This other VAR approach, therefore, imposes sign restrictions on the instantaneous responses of macroeconomic variables to a single policy shock or imposes heterogeneous variance restrictions on the intensity of structural shocks, including single policy shocks.

Regardless of the difference in identification strategy, the exogenous components of the unconventional monetary policy identified in the previous studies are characterized as "unanticipated" unconventional monetary policy shocks. We describe such a shock as "unanticipated" because, in contrast to an "anticipated" policy shock, it provides no prior insight into the current and future paths of the monetary base and unconventional assets ratio. In addition, none of those previous studies took our approach of using the composition of the central bank's assets as an unconventional monetary policy indicator. In this subsection we compare the macroeconomic effects of our anticipated unconventional policy shocks (reported in Subsection 4.3) with the effects of our unanticipated unconventional policy shocks. For the comparison, we adopt the standard recursive VAR approach based on the Cholesky decomposition to extract an unanticipated unconventional policy shock. We employ the recursive approach because the sign restrictions (Schenkelberg and Watzka 2013) and the heterogeneous variance restrictions (Shibamoto and Tachibana 2017) yield qualitatively the same impulse responses as the recursive ones when using the data from Japan.[29]

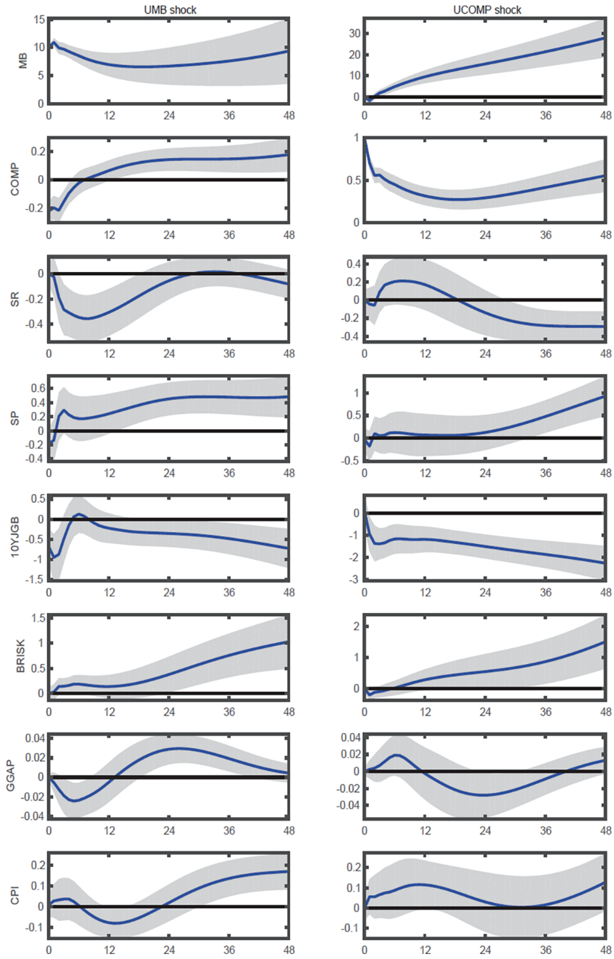
In doing so, we focus on four dimensions in particular: (i) effects on the monetary base, (ii) effects on the interest rate of long-term government bonds, (iii) effects on real economic activity, and (iv) the exogeneity of unconventional monetary policy shocks.

Figure 4 shows estimated impulse responses to the unanticipated monetary base shock (left column) and composition shocks (right column) obtained using the Cholesky decomposition in the eight-variable VAR system, respectively.[30] We find that the evaluation

[29]Schenkelberg and Watzka (2013) and Shibamoto and Tachibana (2017) focused on the BOJ's quantitative easing period from 2001 to 2006. We found, however, that the three alternative approaches yielded qualitatively the same impulse responses across sample periods.

[30]More specifically, in the eight-variable VAR system we order the variables in the conventional manner: output and prices (GGAP, CPI), policy indicators

Figure 4. Impulse Responses to Unanticipated Policy Shocks



Note: Subsection 5.2 discusses the details of identification of the unanticipated monetary policy shocks. Also see the note to Figure 2.

(MB, COMP, SR), and the four financial variables, including the stock price index (SP). For comparison with the anticipated monetary base and composition shocks (i.e., the quantitative and qualitative shocks defined in Section 3), the eight-variable VAR system imposes a recursive restriction for the three monetary policy indicators, in which three unanticipated monetary shocks are determined in the order of an unanticipated policy shock to the monetary base (MB), the of unconventional policy effects heavily depends on whether quantitative and qualitative easing shocks are identified as anticipated (Figure 2) or unanticipated shocks (Figure 4).

5.2.1 Effects on the Monetary Base

The difference in the dynamics of monetary aggregates conditioned on unconventional policy shocks is the most notable when comparing the anticipated and unanticipated shocks. Existing VAR studies identifying unconventional monetary policy shocks as unanticipated shocks have demonstrated a contemporaneous impact on monetary aggregates.[31] Indeed, as shown in the left column of Figure 4, the unanticipated monetary base shock leads to an immediate increase in the monetary base (MB), while the anticipated monetary base shock (i.e., our quantitative easing shock) leads to a gradual increase (see Figure 3).

Also note that, as emphasized in Subsection 3.3, we do not impose any restrictions other than the maximization of the forecast error of the current and future paths of the monetary base when identifying the anticipated monetary base shock by imposing restrictions (16) and (17). Hence, our strategy for identifying the anticipated monetary base shock lets the data speak more for unconventional policy effects on the monetary base, compared with our strategy for identifying the unanticipated monetary base shock. Given this point, the non-contemporaneous response and the gradual increase of the monetary base are the most distinguished features of the anticipated monetary base shock and reflect more of the actual

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unconventional assets ratio (COMP), and the short-term policy rate (SR) (see Section 3). We find that the impulse responses yielded by the short-term policy rate shock (related to the SR) identified in this recursive VAR system are substantially the same as the impulse responses shown in Figure 2. Hence, we do not report them here.

[31] Such a contemporaneous impact on monetary aggregates can be observed in Japanese VAR-based studies: e.g., Iwata and Wu (2006) for M1, and Honda, Kuroki, and Tachibana (2013), Schenkelberg and Watzka (2013), Kimura and Nakajima (2016), Miyao and Okimoto (2017), Shibamoto and Tachibana (2017), and Hayashi and Koeda (2018) for bank reserves. In one VAR-based study on the United Kingdom and United States, Weale and Wieladek (2016) showed a contemporaneous impact on asset purchases. Gambacorta, Hofmann, and Peersman (2014) showed a contemporaneous impact on the total assets of central banks in industrialized countries.

dynamics of the monetary base: the targeted monetary base level is achieved gradually after a policy change announcement, but not abruptly in the announcement.

We can observe the same tendency in the difference between the anticipated composition shock (i.e., our qualitative easing shock) and the unanticipated composition shock: the unanticipated composition shock has an contemporaneous impact on the unconventional assets ratio (COMP), as shown in Figure 4, while the anticipated composition shock does not, as shown in Figure 2.

5.2.2 Effects on Long-Term Government Bond Yields

Some VAR-based studies of the unconventional monetary policy, particularly in the United Kingdom and the United States, have emphasized the policy's causal effect on long-term bond yields (e.g., Kapetanios et al. 2012, Wright 2012, Baumeister and Benati 2013, and Weale and Wieladek 2016).[32] Their motivation stems from the assumption that unconventional policy interventions in the Treasury market would lower the long-term bond yields and then spur real economic activity. Under this assumption they identify an unanticipated policy shock, thereby demonstrating that a stimulative unconventional policy shock would lower the long-term bond yields and narrow the long-short spread of government bonds. Such results for an unanticipated policy shock in the United Kingdom and United States are observed for the anticipated monetary base shock (i.e., our qualitative policy shock) and the two unanticipated shocks in Japan, as shown in the impulse responses of the 10-year government bond yield (10YJGB) (see Figures 2 and 4), but not for the anticipated composition shock (i.e., our qualitative policy shock).

Note that while the two anticipated shocks, our quantitative and qualitative easing shocks, both have substantial impacts on the long-term government bond yield (10YJGB) and long-short spread of the long-term yield and short-term policy rate (SR), the dynamics are quite different: the quantitative easing shock has an immediate and

[32]To examine unconventional policy effects on the long-term bond yields, Wright (2012) employed the heterogeneous variance restriction approach, whereas Kapetanios et al. (2012) and Baumeister and Benati (2013) used the sign restriction approach. Weale and Wieladek (2016) employed four alternative approaches, including the recursive and sign restriction approaches.

persistent effect on the long-term government bond yield and causes a contraction of the long-short spread, while the qualitative easing shock has a slow and less persistent effect and generates a steepening yield curve. The unconventional policy effects on the yield curve depend on the policy tools, as well as the anticipated and unanticipated policy shocks.

5.2.3 Effects on Real Economic Activity

Our quantitative easing and qualitative easing shocks exert opposing effects on not only the long-term government bond yield but also real economic activity. While the quantitative easing shock has contractionary effects on output (GGAP), prices (CPI), and the risk appetite of banks (BRISK), the qualitative easing shock has expansionary effects (left and middle columns of Figure 2). These effects imply that a decrease in the long-term government bond yield stemming from the expansion of the monetary base cannot be presumed to be associated with a rise in real economic activity (Okina and Shiratsuka 2004 and Ugai 2007), and that unconventional policy effects on real economic activity are likely to be heavily dependent on the policy tools.[33]

Both the anticipated and unanticipated composition shocks have expansionary effects on output, prices, and the risk appetite of banks, though the magnitude and persistency of the effects differ between the two composition shocks (right columns of Figures 2 and 4). Regarding the quantitative policy tools, the anticipated monetary base shock has no such expansionary effects (left column of Figure 2), whereas the unanticipated base shock has expansionary effects about one year after the shock arrival (left column of Figure 4).[34]

[33]Okina and Shiratsuka (2004) empirically demonstrated that although the BOJ's quantitative easing was effective in stabilizing market expectations about the future path of short-term interest rates, and thereby brought longer-term interest rates down, these effects were not transmitted to the whole economy in Japan. Ugai (2007) similarly pointed out that the BOJ's quantitative easing had only a limited effect on raising aggregate demand and prices, though it succeeded in lowering the yield curve.

[34]Previous VAR-based studies emphasizing the expansionary effects of the BOJ's quantitative easing policy focused on the quantitative easing from March

5.2.4 Exogeneity of Unconventional Monetary Policy Shocks

Why the unanticipated monetary base shock has expansionary effects remains an open question. To explore this question, we examine the associations among the unanticipated monetary policy shocks and global economic variables out of the eight-variable VAR. The linkages between the Japanese economy and global economy may endogenously determine the unanticipated changes in the policy indicators, including the monetary base. From this analytical viewpoint, we conduct the following system regression of the unanticipated monetary policy shocks on global economic factors:

$$UP_t = R_u^{GF} GF_t + e_t^u, \tag{24}$$

where UP_t denotes the vector variable composed of the unanticipated monetary policy shocks in month t obtained from the eight-variable recursive VAR, and GF_t denotes a vector variable composed of five global economic variables expected to have substantive effects on the Japanese economy: the oil price (OIL), global index of industrial production (GIP), U.S. economic policy uncertainty index (USEPU), U.S. TED spread (USTED), and federal funds rate (FFR). We use the log differences of the oil price and the economic policy uncertainty index, while we multiply the log difference of the global index of industrial production by 100 for illustrative purposes. For the two interest rates, we use their first differences.

In another exercise we examine whether our identified monetary policy shocks can be determined from the global economic variables using the following system regression:

2001 to March 2006 (e.g., Honda, Kuroki, and Tachibana 2013, Schenkelberg and Watzka 2013, Shibamoto and Tachibana 2017, and Hayashi and Koeda 2019). We also examined the impulse responses to the anticipated and unanticipated monetary base shocks obtained during the quantitative easing period from 2001 to 2006. While we found that the anticipated monetary base shock still yielded a gradual increase in the monetary base and exerted contractionary effects on real economic activity even in the quantitative easing period, the unanticipated monetary base shock and contemporaneous increase in the monetary base had expansionary effects, as demonstrated in the previous studies. We also found that both the anticipated and unanticipated composition shocks had expansionary effects in the qualitative easing period.

Table 6. Results for the Regression of Alternative Instruments on Global Economic Factors

	VAR Innovation			Monetary Policy Surprise		
	MB	**COMP**	**SR**	PS^1	PS^2	PS^3
Oil	16.46	–1.00	–0.50	0.40	–0.12	0.47
	(17.89)	(1.90)	(2.29)	(0.61)	(0.47)	(0.32)
GIP	–4.28*	0.13	0.34	–0.04	–0.07	0.07
	(2.34)	(0.20)	(0.31)	(0.08)	(0.06)	(0.05)
USEPU	11.28*	–1.32***	–0.14	0.14	0.09	–0.11
	(5.99)	(0.43)	(0.66)	(0.19)	(0.15)	(0.10)
USTED	–1.83	0.14	1.38	–0.39	0.59	0.19
	(4.73)	(0.54)	(1.41)	(0.30)	(0.41)	(0.13)
FFR	–8.66	–0.12	–0.62	–0.28	–0.25	0.14
	(5.53)	(0.57)	(0.84)	(0.21)	(0.22)	(0.09)
χ^2	8.04	9.87	4.35	3.52	4.30	9.28
	[0.15]	[0.08]	[0.50]	[0.62]	[0.51]	[0.10]

Note: This table shows the estimated coefficients in Equations (23) and (24). Values in parentheses are robust standard errors. *** and * indicate significance at the 1 and 10 percent levels, respectively. χ^2 indicates chi-square statistics (p-values in brackets) resulting from tests of the null hypothesis that the estimated coefficient on the global economic factors are jointly zero.

$$PS_t = R_p^{GF} GF_t + e_t^p, \tag{25}$$

where PS_t represents the three monetary policy surprises, that is, the basis of our qualitative, quantitative, and short-term policy rate shocks.

Table 6 reports the estimation results for the two system equations (24) and (25). As the left panel of Table 6 shows, the unanticipated policy rate shock is not associated with any of the global economic factors. The unanticipated monetary base shock (UMB), on the other hand, is negatively and positively associated with the global index of industrial production (GIP) and the U.S. economic policy uncertainty index (USEPU), respectively. This indicates that the unanticipated monetary base shock increases as an endogenous response to the deterioration in the global economic condition.

The unanticipated composition shock (UCOMP) is also significantly associated with the U.S. economic policy uncertainty index, though in contrast to the unanticipated monetary base shock, its correlation with the index is negative. We find, therefore, that the unanticipated composition shock endogenously increases in response to the improvement in the global economic condition.

In contrast, as the right panel of Table 6 shows, none of the monetary policy surprises are significantly associated with the global economic variables at the 5 percent level of significance. This estimation result ensures that our anticipated monetary policy shocks are exogenous to global economic shocks left out of the VAR system.

The above analysis suggests that the simple use of the unanticipated changes in the unconventional monetary policy indicators (i.e., the monetary base and unconventional assets ratio) can lead to biased estimates of the policy effects (see Gertler and Karadi 2015 for details on the U.S. conventional monetary policy effects). In particular, the unanticipated monetary base shock, which was mainly utilized by Japanese VAR-based studies to measure unconventional monetary policy effects, is negatively associated with the global economic condition, which is not controlled in the VAR model. Hence, unlike the anticipated monetary base shock, the unanticipated shock captures the global economic condition and accordingly cannot be considered a "pure" monetary policy shock. Given this negative association with the global and U.S. economic conditions, the favorable effects of the unanticipated monetary base shock presumably arise from the coordination of central banks around the world, along with the global spillover effects from that coordination, such as the provision liquidity to malfunctioning financial markets. This may be one reason why the unanticipated monetary base shock has expansionary effects on real economic activity.

5.3 Importance of Monetary Policy Surprises

In this subsection, we briefly discuss the importance of combining the monetary policy surprises with the MFEV approach in identifying the quantitative and qualitative policy shocks.[35] To examine

[35] Estimated impulse responses discussed in this subsection are available upon request.

the importance of using the monetary policy surprises, or the three principal components, as external instruments, we apply the MFEV approach directly to the variance-covariance matrix of the reduced-form VAR innovations u_t, but not to that of fitted values generated from system regression (10). Thus, we found that the resulting impulse responses show some implausible size of the effect and unreasonable moves of the monetary policy instruments, implying that the identification based on the VAR residuals would be contaminated by the endogeneity problem.[36]

5.4 Hypotheses about Unconventional Monetary Policy Effects

We have thus far found that our quantitative easing shocks, or the anticipated monetary base shocks, have no favorable effects on the real economy, although they do precipitate decreases in the long-term nominal interest rate, as expected by the BOJ. On the contrary, our qualitative easing shocks, or the anticipated composition shocks, cause favorable effects not only on the long-term interest rate but also on real economic activity. In this subsection we draw from these findings to propose three interrelated hypotheses about the unconventional policy effects, to explore in future research.

One hypothesis holds that the ineffectiveness of quantitative easing shocks can be explained by their effect in raising concern about the future fragility of the real economy. According to Romer and Romer (2000), Ellingsen and Söderstrom (2001), Campbell et al. (2012), Claus and Dungey (2012), Nakamura and Steinsson (2018), and Munakata, Oi, and Ueno (2019), monetary policy actions provide the public with signals of a central bank's information. If the quantitative easing by the BOJ worked as a signal presaging future decreases in output and inflation, this signal would suppress firm investment and wage growth.

The second hypothesis involves economic uncertainty and its effect in instilling caution in real economic activity. Bekaert, Hoerova, and Lo Duca (2013) used stock market option-based implied volatility data, or VIX data, to demonstrate that

[36]See also Kim (2017), Lakdawala (2019), and Kim, Laubach, and Wei (2020) for other recent approaches to identifying multiple policy shocks using external instruments in a VAR setting.

conventional policy easing through reductions in the short-term interest rate decreases economic uncertainty, which in turn leads to favorable effects on the real economy (see also Aastveit, Natvik, and Sola 2017 and Creal and Wu 2017).[37] If the quantitative easing shock elevates economic uncertainty while the qualitative easing shock contributes to its reduction, the difference in the estimated responses of the real economic variables to the two unconventional policy shocks can be explained along this line. Figure 5 reports estimated impulse responses of two uncertainty indices, Japan's monetary policy uncertainty index (JMPU) and the volatility index Japan (JVIX), to the quantitative and qualitative monetary policy shocks. As this figure clearly shows, the quantitative easing shock can be expected to increase both the uncertainty indices, while the qualitative easing shock can be expected to decrease them.[38]

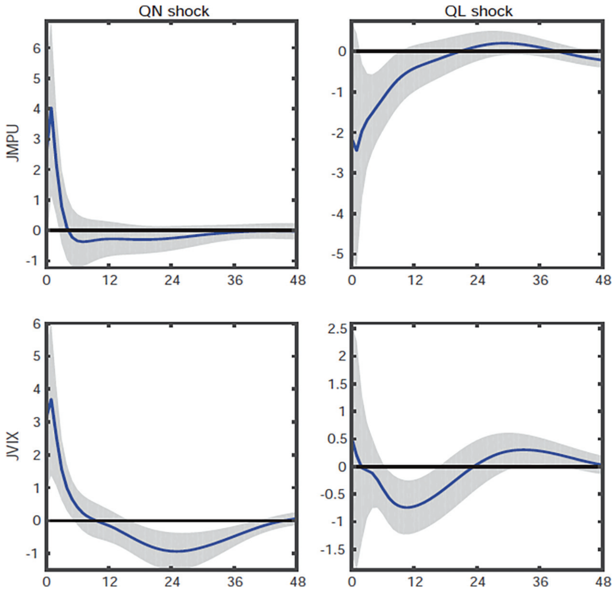
The third hypothesis is based on the growing risk of a government debt crisis comparable to an aggressive expansion of the central bank's balance sheet. Some theoretical studies have pointed out that such a sovereign debt crisis risk can lower not only the government bond yield but also the output (e.g., Kozlowski, Veldkamp, and Venkateswaran 2015), the rate of output growth (e.g., Kobayashi and Ueda 2018), and the price level (e.g., Saito 2020). Given that Japan's gross government debt exceeds 200 percent of the nominal GDP, this third hypothesis, which conjectures a loss of market confidence in government debt that forces the government to collect large tax revenues, seems to convincingly account for the contractionary effects of the quantitative easing.[39]

[37]Gürkaynak and Wright (2012) pointed out that the instability in investors' inflation expectations could stem from a lack of central bank credibility, a problem that might drive a wedge between actual and perceived inflation targets.

[38]We found that the short-term policy rate shock under planning balance sheet operations did not affect the two uncertainty indices, while the policy rate shock followed by the quantitative and qualitative policy shocks decreased them. This result is consistent with the findings reported in Subsections 4.3 and 5.1.

[39]Cúrdia and Woodford (2011) theoretically demonstrated that while quantitative easing is likely to be ineffective, qualitative easing due to the central bank's targeted asset purchases can be effective when financial markets are disrupted (see also Chen, Cúrdia, and Ferrero 2012). In terms of the risk-taking of Japanese commercial banks in lending, Nakashima, Shibamoto, and Takahashi (2020) empirically showed that the BOJ's qualitative easing stimulated bank risk-taking, while the quantitative easing did not.

Figure 5. Impulse Responses of Uncertainty Indicators



Note: The solid lines represent the point estimates of the impulse responses of the monetary policy uncertainty indicator (upper row) and VIX (lower row) in Japan. The impulse responses of the two uncertainty variables are obtained as their responses to the quantitative and qualitative easing shocks, by including each of the indicators into the eight-variable VAR model and employing the identification method developed in Section 3. Also see the note to Figure 2.

6. Conclusion

Previous VAR-based studies have evaluated the central bank's balance sheet operations in an unconventional monetary policy by assuming either that the central bank uses monetary aggregates such as the monetary base and excess reserves as unconventional monetary policy measures, or that the underlying unconventional monetary policy shocks can be captured collectively by a single monetary policy shock. Hence, the previous studies that make these assumptions neglect to distinguish between quantitative and qualitative monetary policy shocks, which prevents them from correctly disentangling the policy effects. In the present study we proposed a new method to separately identify the quantitative and qualitative monetary policy shocks, as well as the short-term policy rate shock, using the unconventional monetary policy the Bank of Japan has kept in place since 1999.

Rather than assuming how a policy indicator responds to an associated policy shock, our method for identifying shocks makes only one assumption, namely, that agents revise their expectations about the path of a policy indicator in accordance with the central bank's announcement of its scheduling action for the indicator. In this sense, our method is agnostic in identifying a particular type of policy shock relating to a monetary policy measure. By demonstrating that the quantitative and qualitative policy measures differ from the policy rate, with neither showing any immediate responses to the central bank's announcement, we have determined that the existing identification methods that cause unconventional policy measures to immediately respond are unsuited for identifying the associated policy shocks.

By defining the two unconventional policy shocks as anticipated shocks, we observe in a robust manner that the qualitative easing shock, which involves a gradual increase in the ratio of the BOJ's unconventional asset to its total assets, yields expansionary effects, whereas the quantitative easing shock, which involves a gradual increase in the size of the BOJ's balance sheet, does not. In future research we will explore why these two unconventional policy shocks yield such different policy effects along the lines suggested in this paper.

Appendix A. Variable Definitions

- Monetary base (MB): seasonally adjusted series, monthly average, retrieved from the Bank of Japan statistics.
- Composition ratio of the BOJ's unconventional assets to total assets (COMP): the BOJ's unconventional assets are defined as the sum of the BOJ's holdings of Japanese government bonds, commercial papers (from February 2009), corporate bonds (from March 2009), asset-backed securities (from July 2003 to September 2006), stocks held as trust property (from November 2002), index-linked exchange traded funds held as trust property (from December 2010), and Japan real estate

investment trusts held as trust property (from December 2010) (end of month), retrieved from the Bank of Japan statistics. The BOJ's total assets (end of month) retrieved from the Bank of Japan statistics.

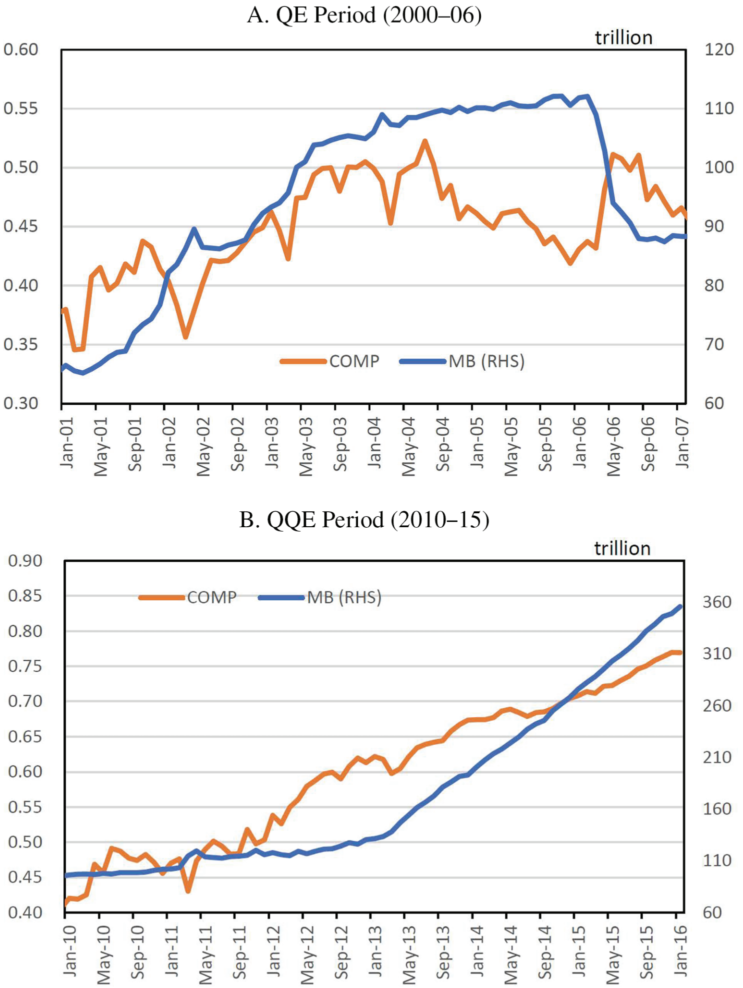
- Short-term policy rate (SR): uncollateralized overnight call rate, monthly average, retrieved from the Bank of Japan statistics.
- Stock price index (SP): Nikkei Stock Average (Nikkei225) index (end of month) retrieved from Nikkei NEEDS FinancialQuest.
- Long-term government bond yield (10YJGB): 10-year Japanese government bond yields (end of month) retrieved from Nikkei NEEDS FinancialQuest.
- Commercial bank holdings of risky assets (BRISK): difference between the risky assets and safe assets held by commercial banks. Risky assets are defined as the sum of the commercial bank holdings of bank loans, stocks, corporate bonds, and foreign securities (end of month) retrieved from the Bank of Japan statistics. Safe assets are defined as the commercial bank holdings of Japanese government bonds (end of month), retrieved from the Bank of Japan statistics. We obtain seasonally adjusted series using the Census X-12.
- GDP gap (GGAP): Quarterly GDP gap series retrieved from the Bank of Japan statistics and interpolated to obtain monthly observations.
- Consumer price index (CPI): consumer price index, excluding fresh foods (2015=100), consumption-tax-adjusted series for the period from April 1998 to December 2014, retrieved from the Ministry of Internal Affairs and Communications. We obtain seasonally adjusted series using the Census X-12.
- Oil price (OIL): Crude Oil Prices: West Texas Intermediate (WTI) (monthly average) retrieved from Federal Reserve Economic Data (FRED).
- Global index of industrial production (GIP): World Industrial Production, excluding construction (Import-Weighted, 2010=100), retrieved from Haver Analytics.
- U.S. economic policy uncertainty index (USEPU): A news-based policy uncertainty index retrieved from the following website: http://www.policyuncertainty.com/.

- U.S. TED spread (USTED): the spread between the three-month LIBOR based on U.S. dollars and three-month Treasury bill (monthly average) retrieved from FRED.
- Federal funds rate (FFR): effective federal funds rate (monthly average) retrieved from FRED, shadow federal funds rate series of Wu and Xia (2016) from January 2009 to November 2015, retrieved from Jing Cynthia Wu's website: https://sites.google.com/view/jingcynthiawu/shadow-rates.
- Japan's monetary policy uncertainty index (JMPU): Japan's Monetary Policy Uncertainty Index constructed by Arbatli et al. (2022), retrieved from the following website: http://www.policyuncertainty.com/.
- Japan's volatility index (JVIX): Volatility Index Japan, retrieved from the following website: http://www-mmds.sigmath.es.osaka-u.ac.jp/structure/activity/vxj.php? (monthly average).

Appendix B. Development of Monetary Base and Unconventional Asset Ratio

We plot the two policy instruments of the monetary base (MB) and the unconventional asset ratio (COMP), focusing on the two distinct periods: the first half of the 2000s for the QE and the 2010s for the QQE in Figure B.1. The monetary base and risky asset ratio have enough variation to allow us to identify two different shocks, although there are some periods when the two indicators share a trend. In fact, as the left-hand panel shows, when the first QE was implemented in the 2000s, the two indicators show a large variation. For example, when the BOJ started the QE, the risky asset ratio increased swiftly, but the monetary base increased gradually. On the other hand, when the BOJ exited the QE in 2006, the MB decreased while the COMP increased. This is partly because the reduction of the balance sheets was mainly conducted through the reduction of holdings of short-term government debts. From these examples, we can infer that the MB and COMP reflect different information about the monetary policy stance. In addition, in the 2010s, the MB and COMP show different changes depending on the

Figure B.1. Monetary Base and Risky Asset Ratio



Note: COMP indicates the ratio of the amount of unconventional assets to the BOJ's total assets. MB indicates the monetary base in trillion yen.

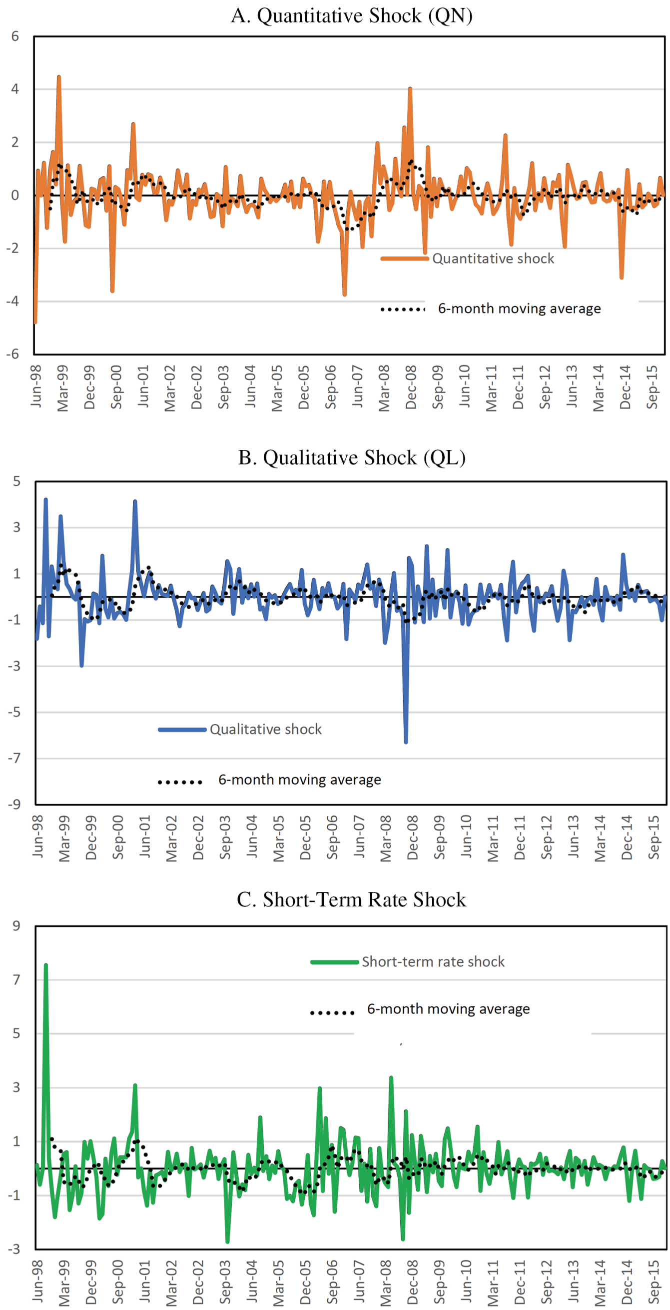
policy actions that the BOJ took. For example, before the introduction of the QQE in 2013, the COMP increased over time due to an increase in the purchase of long-term government bonds, ETFs, and real estate investment trusts. During this period, the MB only gradually increased. On the other hand, after 2015, both the MB and

COMP have increased almost monotonically. However, even after the introduction of the QQE, especially in 2014, the COMP had remained almost flat, while the MB continued to increase substantially. These observations clearly show that the COMP and MB do not always share a trend; rather, they show a wide variation depending on periods.

Appendix C. Estimated Monetary Policy Shocks

The estimated shocks are shown in Figure C.1. There are several observations worth mentioning. First, as Figure C.1 shows, the quantitative shock (QN) saw a significant negative value when the BOJ exited from the zero interest rate policy in August 2000. In addition, in March 2001, when the BOJ decided to implement the quantitative easing (QE), the QN shock reached its peak. The QN also captures the timing when the BOJ exited the QE and increased the policy rate in July 2006. After the GFC, the BOJ expanded its balance sheets immediately and continued the expansion of QE and QQE in the 2010s. In this period, the QN shocks stayed positive on average. As for the qualitative (QL) shock, there was a sharp hike in the QL shock in March 2001 when the BOJ started the QE. In the monetary policy meeting in March 2001, the BOJ also decided to increase the purchasing amount of long-term bonds, which we categorized as unconventional assets. Therefore, the QL shock tracks the change in asset composition successfully. In addition, in October 2008, the QL shock dropped and increased substantially in the next period. This swing reflects the aggressive monetary policy stance of the BOJ to address the turmoil in the GFC. In the meeting on October 14, 2010, the BOJ decided to increase especially the provision of short-term liquidity. This policy decreased the share of unconventional assets temporarily. However, in the later meetings, the BOJ decided to increase the purchasing amount of longer-term bonds, which is reflected in the hike in the QL shock. Moreover, in April 2013, when the BOJ announced the introduction of QQE, the QL shock increased substantially. In the meeting, the BOJ decided to increase the purchase of ETFs and other risky assets. Overall, the development of the estimated shocks indicates that our identification methodology works well.

Figure C.1. Estimated Monetary Policy Shocks



Note: The figure shows estimated monetary policy shocks using monetary policy surprises.

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Order Matters: An Experimental Study on How Question Ordering Affects Survey-Based Inflation Forecasts*

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Policymakers often rely on survey data when gauging expectations. To know the limits of survey data is thus crucial. We look at inflation expectations as measured through the Deloitte CFO Survey Switzerland and respondents' sensitivity to question ordering thereof. We investigate whether forecast inconsistencies—the discrepancies between point and density forecasts—as well as forecast accuracy change significantly depending on whether the point forecast or the density forecast is asked first. We find that forecast inconsistencies are sizable and order matters. Density forecasts seem to be less affected by question ordering than point forecasts and more accurate than point forecasts.

JEL Codes: E31, E37, E58.

1. Introduction

Expectations are key variables in macroeconomics. However, they are hardly measurable. One way to gauge expectations of households, professional forecasters, or firms is in the form of surveys.

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At least since Lucas (1972), economists have been widely assuming rational expectations of agents regarding future macroeconomic variables such as income and inflation. In other words, expectations are generally thought to be objectively and optimally formed given all available information. This also means that agents are assumed to be able at all times and under any circumstances to formulate clear and consistent answers. However, cognitive science has documented that seemingly innocuous factors such as purpose of the surveyor, topics covered, ordinary conversational norms, question length, wording and ordering, and many others can have a significant impact on survey responses; see, e.g., Sudman, Bradburn, and Schwarz (1996) or Tourangeau, Rips, and Rasinski (2000) for a review on the cognitive psychological theory behind surveys. These effects are known as *question effects*. Schuman and Presser (1981) provide insights into many empirical studies and experiments on question effects.

Recent review papers and books surveying the state of expectations' measurement, the literature on the role and nature of expectations in macroeconomics and finance, as well as a growing number of measurement efforts signal that the view is also changing in the economics profession (see, among others, Carroll 2017; Coibion et al. 2018; Coibion, Gorodnichenko, and Kumar 2018; Gennaioli and Shleifer 2018; Manski 2018).

One domain of expectations that has gained increased attention is the one of inflation expectations. For a recent review, see, for instance, Coibion et al. (2020). Inflation expectations are considered an important determinant in the transmission of monetary policy and are therefore closely monitored by central banks. However, to be a useful policy tool, it is important for policymakers to have reliable and robust data on inflation expectations. Knowing about and possibly avoiding question effects and other sources of measurement errors in inflation expectations is therefore crucial.

This paper addresses question effects in inflation expectations. To the best of our knowledge, it is the first one to study question ordering in inflation expectations. We analyze whether question ordering is crucial for forecast inconsistencies, i.e., the discrepancies between point forecasts and measures of central tendency derived from density forecasts, in inflation expectations. To do so, we make use of the Deloitte CFO Survey Switzerland, which contains two questions about expected inflation in two years' time: the first question asks for a point forecast, and the second question asks for a density forecast. From 2014:Q4 until 2017:Q3 we set up an experiment and randomly assigned the order of these two questions to each of the survey respondents. We first assess whether there exists a persistent discrepancy—a forecast inconsistency—between point forecasts and measures of central tendency derived from density forecasts using non-parametric and parametric techniques. We then study whether these forecast inconsistencies change significantly depending on the specific order in which these two questions are asked, i.e., point forecast first and density forecasts second or vice versa. Finally, we analyze whether the potentially distortional effects of question ordering on consistency are relevant when thinking about forecast accuracy.

We find that (i) forecast inconsistencies are sizable in the data: approximately 18 to 25 percent of all forecasts are inconsistent. We also find that (ii) question ordering matters. Asking for the density forecast before the point forecast results in an approximately 5 percentage point increase in inconsistencies on average, whereby the question ordering affects mainly the answers to the point forecast, while the answers to the density forecast seem to be almost unaffected. In addition, (iii) forecasts are not equally distributed below and above their thresholds of consistency: central tendency measures derived from density forecasts generally reflect lower inflation expectations than point forecasts. This difference is statistically significant mostly for those who are asked the density forecast first. Finally, (iv) the answers to the density forecast question yield higher forecast accuracy than the answers to the point forecast question.

Our paper is in particular related to the following two strands of literature: First, there exists an empirical body in the economic literature that points towards the presence of question effects in inflation expectations. For instance, Bruine de Bruin et al. (2012) study the effect of question wording regarding inflation expectations of households[1] and Arioli et al. (2017) report that survey design such as wording, but also sample design and interview methodology, affect

[1]Initial results can be found in Van der Klaauw et al. (2008) and Bruine de Bruin et al. (2010).

responses to inflation expectations. Coibion et al. (2020) also report the sensitivity of inflation expectations to the design of questions, and Niu and Harvey (2021) analyze how context influences people's judgments in inflation rate surveys.

Second, one strand of literature studies forecast biases and inconsistencies by comparing point forecasts with density forecasts.[2] That point forecasts and measures of central tendency derived from density forecasts do not always match—so-called forecast inconsistencies—was acknowledged first by Engelberg, Manski, and Williams (2009). They assessed consistency using both a non-parametric and a parametric approach. They found that among those point forecasts that are inconsistent with their respective density forecast, a higher proportion underestimates inflation and overestimates GDP growth. Other contributions also point towards the fact that professional forecasters are not necessarily internally consistent and tend to provide point forecasts that are rosier than their density forecast; see, e.g., Garcia and Manzanares (2007), Boero, Smith, and Wallis (2008), or Clements (2009). The early literature comparing point and density forecasts explored uncertainty. Zarnowitz and Lambros (1987) found that the standard deviation of point forecasts tends to understate the mean dispersion of individual density forecasts, although they remain generally positively correlated. Giordani and Söderlind (2003) followed by comparing and discussing the relevance of both measures plus a third one, the variance of aggregate histograms, in capturing uncertainty.[3] They argue that they are all relevant depending on what one wishes to capture and find that disagreement is a reasonable proxy for uncertainty.

The remainder of this paper is structured as follows. Section 2 describes the data and our experiment. Section 3 investigates the effects of question ordering on forecast inconsistencies using non-parametric and parametric methods, and shows and discusses the results. Section 4 analyzes forecast accuracy. Section 5 provides a

[2]For a survey on density forecasts, their applications, evaluations, and limits, see Tay and Wallis (2000).

[3]Aggregate histograms are obtained by averaging over individuals the probability assigned to each bin.

discussion on the interpretation and the limitations of our results. Section 6 concludes.

2. Data

2.1 The Deloitte CFO Survey

In this paper, we use data from the Deloitte CFO Survey conducted in Switzerland at a quarterly frequency since the third quarter of 2009. The survey covers the views of chief financial officers (CFOs) and group financial directors of companies in Switzerland from all relevant sectors on their outlook for business, as well as on financing, risks, and strategies. According to Deloitte, the sample is representative of the Swiss economy.

Each quarter, in March, June, September, and December, around 350 firms are contacted via e-mail to fill in the questionnaire. The number of respondents varies each quarter but is usually over 100 firms. The panel of participating CFOs changes over time. According to Deloitte, each quarter, 10 to 30 respondents are completely new to the sample, and the majority are respondents who either have been taking part for only a few surveys or who do not participate regularly. However, for reasons of anonymity, Deloitte does not provide us with the individual identifiers. We are thus unable to exploit any possible panel structure. Thus, we cannot track CFOs over time, and we treat our data set as a repeated cross-sectional study.

The survey is conducted online. It covers 20 questions that recur each quarter and approximately 10 questions unique to the financial conditions of the previous quarter. On the computer screen, the participants only see one question at a time. We thus know the order in which the questions are being presented to the interviewees. The participants do not have to provide answers for all the questions to complete the survey, and are allowed to go back and forth and edit their previous answers.

Since our focus lies on inflation expectations, we will mainly look at the following two questions:

1. In two years' time, what annual rate of inflation, as measured by the Swiss consumer price index, do you expect?

2. In two years' time, where do you expect the annual rate of inflation (Swiss consumer price index) to be?

$$(-\infty, -4], (-4, -2], (-2, -1], (-1, 0], (0, 1], (1, 2], (2, 4], (4, +\infty)$$

The first question asks for a point estimate of two-year-ahead annual inflation rate (in percent), while the second offers a fixed number of intervals for the same rate, to which respondents are requested to assign probabilities. These intervals together form a symmetric eight-bin centered histogram. At the interval level, we interpret missing values as zeros. If the assigned probabilities do not add up to 100 percent, we normalize them so that they add up to 100 percent.[4] Moreover, for our analysis we exclude observations where either answer is missing. Appendix Section A.1 provides additional information about missing observations, the assigned probabilities, and their normalization.[5]

2.2 The Experiment

As of 2014:Q1 we implemented the following experiment together with Deloitte: until then, questions 1 and 2 were always presented in the same order—point forecast first, density forecast second. From 2014:Q1 the order was assigned randomly to participants. The implementation took some time. Until 2014:Q3 we had to assign the ordering manually as follows: First, participants were asked about the point forecast, then about their density forecast. We then switched the ordering after approximately 50 percent of the CFOs whom we expected to participate in the respective quarter concluded the survey. We are fully aware that these two groups might have had quite different information sets each quarter. This in turn could have influenced their answers on inflation expectations. We therefore treat 2014:Q1 until 2014:Q3 as a trial period. From 2014:Q4 onwards, the computer program was adjusted such that the order of the two questions was completely randomized with no manual interference,

[4] All our results are robust to excluding the observations for which the probabilities do not add up to 100 percent.

[5] Appendix Table A.1 provides summary statistics about point forecasts, density forecasts, and firm characteristics.

giving each respondent a true 50 percent chance of seeing the question asking for the point forecast before the question asking for the density forecast or the other way around on their computer screen. The following analysis of inconsistency of the forecasts will be based on the sample with complete randomization, i.e., from 2014:Q4 until 2017:Q3.[6]

3. Forecast Inconsistencies

3.1 Methodology

Generally, a forecaster is said to be internally consistent if he or she gives the same answer to two identical questions asked differently. In our case, each point forecast can reasonably be thought to match some statistic derived from the respective subjective probability distribution function underlying expectations over future inflation, which in turn should be summarized in each density forecast. In other words, if we knew each respondent's forecasting model and the statistic reported as the point forecast, we should be able to map density forecasts into point forecasts almost exactly. We could then confidently consider any difference as a *forecast inconsistency*. Unfortunately, with the data at hand we need to make assumptions to match density forecasts with their respective point forecasts.

There are two approaches to assessing consistency between point forecasts and density forecasts: the non-parametric and the parametric one. The non-parametric approach binds consistency by using the edges of each interval given in the survey but makes no further assumption regarding the underlying subjective distribution. The parametric approach, however, explicitly states the shape of the distribution and may rely on fitting techniques to obtain its parameters such as the mean and variance. The fundamental difference between these two methods lies in whether one wishes to assume how the probability mass is distributed *within* each bin. We therefore face a trade-off: While the non-parametric approach provides

[6]Deloitte modified its survey after 2017:Q3: Not only did the frequency change (from quarterly to biannually), but the questions were adjusted to be more in line with CFO surveys the company conducts abroad. We stopped our experiment at that time for this reason.

a more agnostic assessment, it does not give any information as to the *degree* of inconsistency one forecaster might show. In particular, under the non-parametric approach, we are only able to say whether a forecast is consistent or not, whereas the parametric approach tells us exactly by how much.

As for the parametric approach, we will follow Zarnowitz and Lambros (1987). This widely applied approach only assumes that the probability mass of density forecasts is located at the center of each bin. This allows us to compute the *midpoint* of each density forecast, i.e., its subjective mean.[7] A technical requirement however is to close the interval of the first and the last bin. In Question 2 (see Section 2) the first and the last bin is formulated as a one-sided open interval. To close the interval, we attribute the value -6 and 6, as it reproduces the length of 2 percentage points of inflation of the intervals, respectively, following and preceding them.[8] A drawback of this methodology is that it over-evaluates the variance under bell-shaped densities. In this respect, the so-called Sheppard's correction may help to obtain a more realistic estimate of the variance but is only computable if the bins are of the same size, which is not the case in the Deloitte CFO Survey. Notwithstanding, because we are not required to accurately evaluate the uncertainty surrounding density forecasts in our setup, we chose to follow the above-mentioned approach for its readability and simplicity.[9]

The following example should illustrate the difference between both approaches: If a forecaster assigns the probabilities 0.3, 0.4, 0.2, 0.1 to the bins $(-1, 0]$, $(0, 1]$, $(1, 2]$, $(2, 4]$, respectively, and 0 elsewhere, then the non-parametric approach binds midpoint consistency between $-1 \cdot 0.3 + 0 \cdot 0.4 + 1 \cdot 0.2 + 2 \cdot 0.1 = 0.1$ and $0 \cdot 0.3 + 1 \cdot 0.4 + 2 \cdot 0.2 + 4 \cdot 0.1 = 1.2$. The forecast is then considered consistent if the point forecast lies within $(0.1, 1.2]$. The

[7] Assuming the mass is uniformly distributed within each bin produces equivalent midpoint estimates.

[8] This choice is virtually irrelevant, since only 2.5 percent of the treatment sample assigned a probability greater than or equal to 10 percent to either of the extreme bins. All our results remain robust for other choices.

[9] Appendix Section A.4 describes an alternative approach which consists in fitting normal distributions to individual density forecasts by numerical optimization as in Giordani and Söderlind (2003). All our results are robust to such methodology, as shown in Section A.6 of the appendix.

lower (upper) bound accounts for the possibility that the forecaster always considered the lowest (highest) value of the bin while reporting the probabilities. By contrast, the parametric approach infers that the subjective midpoint be exactly $-0.5 \cdot 0.3 + 0.5 \cdot 0.4 + 1.5 \cdot 0.2 + 3 \cdot 0.1 = 0.65$, because it supposes that the forecaster always and exclusively considered the center of the bin. Any deviation of the point forecast from this value can then be associated with inconsistency.

As the point estimate question does not specify what statistic of the subjective probability distribution the respondent should report, although the use of the word "expect" points towards the use of expectation or mean as the relevant predictor, forecasters might report the median of their subjective distribution as their point forecast rather than the midpoint. To account for this case, we computed subjective medians as follows. In the non-parametric case, the subjective median is the first interval itself whose cumulative probability is 50 percent or more. In the parametric case, it is the middle of the same interval. By identifying the median in this way, we allow for potentially asymmetric density forecasts. Equivalently, one might be interested in assessing mode consistency. Because this requires further assumptions, we detail such analysis and show the robustness of our results thereto in Table A.4 in Section A.6 of the appendix.

3.2 Non-Parametric Approach

Table 1 displays the results of the non-parametric approach. For each quarter of the experiment and by question ordering, it shows the percentage of respondents that gave a point forecast respectively within, below, or above their respective interval of consistency, evaluated according to the above-described non-parametric subjective midpoints and according to the non-parametric subjective medians. We denote such percentages by λ_i^k, where $i = P, D$ stands respectively for the group of respondents who were asked for a point forecast or a density forecast first, and $k = c, b, a$ stands respectively for consistent, below, and above. The last row depicts the pooled sample.

Focusing on midpoints, we observe a proportion of consistency that ranges from 74.5 to 96.1 percent for the P group, and from

Table 1. Midpoint and Median Forecast Consistency by Question Ordering

Quarter	Subjective Midpoint						Subjective Median					
	Consistent		Below		Above		Consistent		Below		Above	
	$\boldsymbol{\lambda}_P^c$	$\boldsymbol{\lambda}_D^c$	$\boldsymbol{\lambda}_P^b$	$\boldsymbol{\lambda}_D^b$	$\boldsymbol{\lambda}_P^a$	$\boldsymbol{\lambda}_D^a$	$\boldsymbol{\lambda}_P^c$	$\boldsymbol{\lambda}_D^c$	$\boldsymbol{\lambda}_P^b$	$\boldsymbol{\lambda}_D^b$	$\boldsymbol{\lambda}_P^a$	$\boldsymbol{\lambda}_D^a$
2014:Q4	80.3	82.1	9.8	1.8	9.8	16.1	72.1	71.4	14.8	1.8	13.1	26.8
2015:Q1	81.4	66.7	8.5	10.5	10.2	22.8	74.6	73.7	16.9	12.3	8.5	14.0
2015:Q2	74.5	62.0	14.5	8.0	10.9	30.0	67.3	60.0	21.8	4.0	10.9	36.0
2015:Q3	83.7	73.1	4.1	3.8	12.2	23.1	79.6	73.1	8.2	5.8	12.2	21.2
2015:Q4	77.2	71.9	17.5	1.8	5.3	26.3	78.9	73.7	15.8	1.8	5.3	24.6
2016:Q1	87.7	80.4	8.8	5.9	3.5	13.7	77.2	78.4	12.3	7.8	10.5	13.7
2016:Q2	76.5	81.5	17.6	3.7	5.9	14.8	52.9	64.8	29.4	7.4	17.6	27.8
2016:Q3	86.0	71.2	6.0	5.8	8.0	23.1	84.0	59.6	8.0	13.5	8.0	26.9
2016:Q4	80.4	81.3	7.8	4.2	11.8	14.6	80.4	79.2	5.9	4.2	13.7	16.7
2017:Q1	80.4	76.4	5.9	0.0	13.7	23.6	76.5	72.7	9.8	1.8	13.7	25.5
2017:Q2	75.6	79.6	8.9	2.0	15.6	18.4	68.9	75.5	17.8	6.1	13.3	18.4
2017:Q3	96.1	78.0	2.0	0.0	2.0	22.0	80.4	70.0	9.8	2.0	9.8	28.0
Pooled	81.6	75.3	9.4	4.0	8.9	20.8	74.4	71.0	14.3	5.7	11.3	23.3

Note: Each cell represents the percentage λ_i^k of respondents from group $i = P, D$ falling in the category $k = c, b, a$, for the quarter in row. The subscript P (D) denotes the respondents who were asked for a point (density) forecast first. The superscripts c, b, a respectively denote whether the point forecast lies within, below, or above its level of consistency.

62 to 82.1 for the D group. Quarterly consistency between the groups correlates by 19.4 percent, which indicates that time-varying macro factors exert a common pressure on consistency, although in a relatively low manner. Looking at the pooled sample tells us that those respondents who were asked for the point forecast before the density forecast were consistent in 81.6 percent of the cases, whereas those who were asked for the density forecast first were consistent in 75.3 percent of the cases. In other words, consistency (as defined by the non-parametric approach) of the P group exceeded that of the D group, on average, by a 6.3 percentage points margin. This difference of 6.3 percentage points is statistically significant at the 1 percent level as seen in Table A.9 in Section A.7 of the appendix.

More interestingly, a quick inspection of inconsistent forecasts reveals that the proportion of point forecasts that lie above and below their respective level of consistency is quite heterogeneous and depends on question ordering. For those who were asked for a point forecast first, the amount of under-evaluations of point forecasts relative to density forecasts ranges between 2 and 17.6 percent, while this amount ranges only between 0 and 10.5 percent for the other group. Conversely, the proportion of over-evaluated point forecasts varies from 2 to 15.6 percent for the P group, while it goes from 14.6 to as much as 30 percent for the D group.

In total, those who saw the question asking for a point forecast first understated inflation slightly more often (9.4 percent below versus 8.9 percent above), while the others almost systematically overstated inflation (4 percent below versus 20.8 percent above). In other words, being asked for the density forecast before the point forecast not only increases the amount of inconsistency but also makes it more likely for the point forecast to overstate the level of inflation as suggested by the density forecast.

The scrutiny of median non-parametric consistency gives the same general message. Interestingly, consistency occurs less often in the data when we evaluate consistency based on the relationship between point forecasts and subjective medians. This may indicate that forecasters actually link their point forecast to the mean of their density forecast rather than to the median thereof. Interestingly, Meyler and Rubene (2009) and Stark (2013) show a great reliance on judgment when producing a forecast and show that forecasters are likely to be heterogeneous. The European Central Bank (ECB) and the Federal Reserve Bank of Philadelphia respectively issued a special questionnaire to gauge how their panelists compute and provide their predictions. The ECB reports that interviewees on average weight *judgment* as contributing up to 40 percent of their forecast. Approximately 80 percent of the respondents produce their density forecast solely based on judgment. When asked about which statistic they refer to for their point forecast, approximately 75 percent checked the mean, 20 percent the median, and 7 percent the mode. The Federal Reserve Bank of Philadelphia presents a similar picture: 80 percent of their interviewed panelists revealed that they rely on both mathematical models and judgment to form their forecasts. Notwithstanding, the P group remains more consistent than the D group by 3.4 percentage points. However, this difference is not significant, as we show in Table A.9 in the appendix. Moreover, the pattern in the discrepancies between excessively high and excessively low point forecasts as a function of question ordering is preserved.

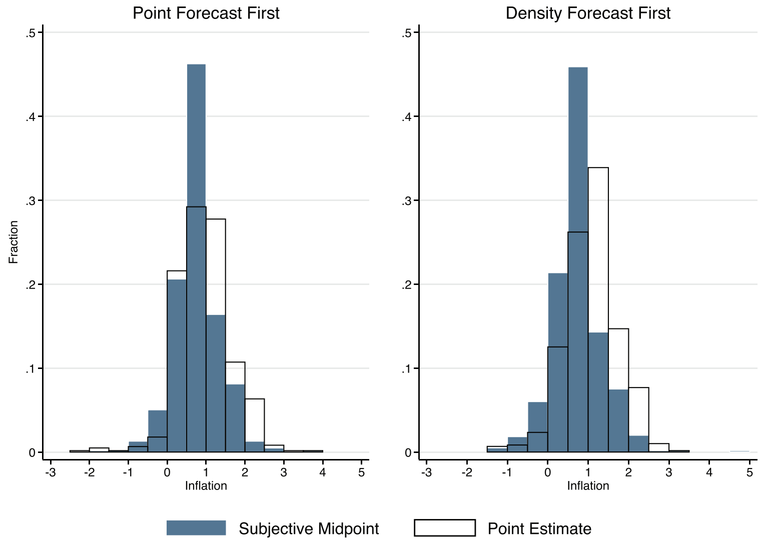
Overall, these results provide evidence that question ordering matters. In particular, asking for a point forecast before a density forecast seems to result in fewer occurrences of inconsistency. Furthermore, it appears that asking first for a point (density) forecast produces a slight (strong) tendency to report point forecasts reflecting a lower (higher) level of inflation than the respective subjective midpoints and medians. Therefore, our non-parametric assessment of consistency indicates that the effect of question ordering is twofold, for it both strongly affects the *amount* of inconsistencies and their *nature*.

3.3 Parametric Approach

The parametric approach allows us to derive from the density forecasts some measures of central tendency that are in levels. However, as detailed above, it requires assumptions. The measure we are focusing on in our analysis is the midpoint, i.e., the subjective mean of density forecasts under the assumption that the probability mass is exactly located at the center of each bin.

Figure 1 plots, for each question ordering, the histogram of subjective midpoints against the histogram of point forecasts in the

Figure 1. Point Forecasts and Subjective Midpoints by Question Ordering

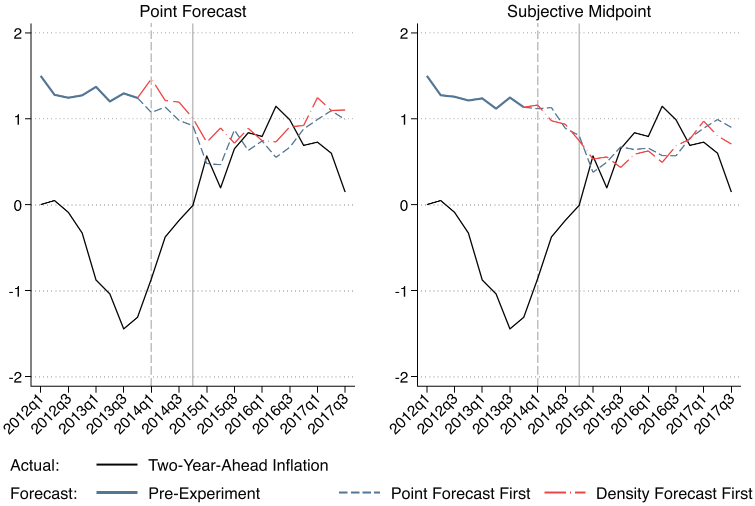


Note: The figure plots, for each group, the fraction of respondents (from 2014:Q4 to 2017:Q3) who reported a forecast corresponding to a certain level of inflation (in bins of size 0.5 percentage point), either directly (point forecast, in white) or indirectly (subjective midpoint derived from density forecast, in blue).

pooled sample (from 2014:Q4 to 2017:Q3). In particular, it shows the fraction of respondents who reported a forecast corresponding to a certain level of inflation (in bins of size 0.5 percentage point), either directly (subjective point forecasts, in translucent white) or indirectly (subjective midpoints, in blue).

On the one hand, it appears that the distribution of subjective midpoints is quite homogeneous between the groups (i.e., comparing the left and the right panel), with a fraction of almost 70 percent of all midpoints being comprised between 0 and 1 percent of inflation. On the other hand, however, it seems that the distribution of point forecasts shifts towards the center of the distribution of subjective midpoints when one jumps from the right to the left panel. Indeed, while approximately 50 percent of point forecasts lie between 0 and 1 percent of inflation for the P group, only approximately 35 percent do for the D group.

Figure 2. Quarterly Point Forecasts and Subjective Midpoints



Note: The dashed vertical line marks the implementation of the experiment, while the solid vertical line marks the starting point of our analysis.

Clearly, forecasters being asked for the point forecast before the density forecast generally give a point forecast that is more in line with the density forecast than forecasters facing the opposite ordering. In other words, we can already confirm the result from the non-parametric analysis, that forecasters tend to be less consistent when they first see the question about the density forecast.

Figure 2 breaks down point forecasts and subjective midpoints by group and quarterly averages, and plots them as a time series along with actual inflation. The dashed vertical line marks the implementation of the experiment (trial period), while the solid vertical line marks the starting point of our analysis (i.e., from 2014:Q4 to 2017:Q3). The black solid line is year-on-year inflation, lagged two years. The blue solid line represents quarterly averages of point forecasts, respectively subjective midpoints for the pre-experiment period. The blue dashed line depicts quarterly averages of point forecasts, respectively subjective midpoints for the P group and the red dashed-dotted line the ones for the D group. Recall that before the implementation of the experiment (i.e., from 2012:Q1 to 2014:Q1), point forecasts were always asked before density forecasts. The blue dashed line, which shows the results of the group that sees the point forecast question first (P group), can therefore be expected to follow the pattern of the solid blue line (like a control group)—any deviation of the red dashed-dotted line from the blue dashed line can thus be interpreted as the effect of flipping the question ordering (i.e., the treatment effect). Comparing the point forecasts between the two groups shows that the average point forecast of the D group is somewhat persistently higher than that of the P group (Figure 2, left panel). For the average midpoint, one can barely distinguish the two series (Figure 2, right panel).

Table 2 formalizes these observations for the pooled series. First, it shows the sample mean point forecast of the D and the P group and the respective standard deviation. The 0.16 percentage point difference in the mean point forecasts between the two groups is statistically significant, while the 0.94 ratio between their respective standard deviations is not.[10]

Second, Table 2 shows the mean probabilities assigned to each bin for both groups. The mean probabilities assigned to each bin can never be said to differ significantly between the groups. However, we reject equal variance of the assigned probability between groups for all but two of the eight bins. Interestingly, these two bins together comprise inflation from above zero to below 2 percent, and account on average for more than 70 percent of cumulated probability. Given that the Swiss National Bank defines price stability as an annual inflation rate below 2 percent and non-negative, this result suggests that credibility by forecasters about the capacity of the central bank to achieve its target is not affected by question ordering. In other words, inflation expectations seem to be too well anchored regarding "normal territories" for question ordering to affect the

[10]In Section A.9 of the appendix, we compare one-year-ahead exchange rate point forecasts, which are also elicited in the survey, between the two groups. This placebo test aims at putting the significant differences found in Table 3 in perspective: Significant differences in exchange rate forecasts between the two groups would cast doubt on the validity of our experiment. Table A.11 in the appendix shows no such pattern and strengthens the direct link between inflation-related differences and question ordering.

Table 2. Comparison between Groups

Variable	Mean			Std. Dev.		
	$\boldsymbol{\mu_D}$	$\boldsymbol{\mu_P}$	$\boldsymbol{\mu_D - \mu_P}$	$\boldsymbol{\sigma_D}$	$\boldsymbol{\sigma_P}$	$\boldsymbol{\sigma_D/\sigma_P}$
Inflation Expectations						
Point Forecast *Two-years-ahead inflation expectation*	0.92	0.76	0.16*** (4.3)	0.63	0.67	0.94 (0.9)
Density Forecast *Probability that two-years-ahead inflation lie within. . .*						
$(-\infty, -4]$	0.11	0.07	0.04 (0.8)	1.29	0.46	2.8*** (8.0)
$(-4, -2]$	0.45	0.64	−0.19 (−1.5)	1.59	2.75	0.58*** (0.3)
$(-2, -1]$	3.46	3.19	0.27 (0.6)	8.67	7.60	1.14*** (1.3)
$(-1, 0]$	17.49	16.19	1.3 (1.3)	18.28	16.33	1.12** (1.2)
$(0, 1]$	47.27	47.54	−0.27 (−0.2)	24.95	24.49	1.02 (1.0)
$(1, 2]$	24.37	25.82	−1.45 (−1.2)	20.82	21.12	0.99 (0.9)
$(2, 4]$	6.14	5.93	0.21 (0.4)	10.02	9.18	1.09* (1.2)
$(4, +\infty)$	0.71	0.62	0.09 (0.4)	4.46	2.85	1.56*** (2.5)
Subjective Midpoint	0.66	0.68	−0.02 (−0.6)	0.61	0.60	1.03 (1.1)

Note: This table shows the sample mean (μ_i) and the sample standard deviation σ_i, from group $i = P, D$ for the sample between 2014:Q4 and 2017:Q3, i.e., during the experiment. $P(D)$ denotes the respondents who were asked for a point (density) forecast first. There are 637 (631) observations in the P (D) group. t and F statistics respectively for the mean- and variance-comparison tests are given in parentheses. Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

variability of its associated probability (which, as we noted earlier, is centered around the same value for both groups). What question ordering does seem to affect is the (lack of) consensus as to the probability of rarer events, i.e., disinflation and high inflation. Nonetheless, identifying a pattern is difficult, for the significant differences in standard deviations between the two groups only reflect a cumulated probability of 30 percent.

Third, Table 2 reports the sample mean subjective midpoints of the density forecasts for both groups. The –0.02 percentage point difference in the sample mean midpoint between the two groups is not statistically significant.

Overall, the answers to the density forecast question seem to be less affected by question ordering than the answers to the point forecast question.

Nevertheless, to give a formal appraisal of the average treatment effect and its significance, we need to go one step further and compare the average inconsistencies *between* the two orderings. This is comparable to a difference-in-differences approach: because point forecasts are on average higher than subjective midpoints for both groups as shown in Figure 2, only the difference between the respective discrepancy captures the causal effect of question ordering. To this end, Table 3 summarizes by quarter the number of respondents N_i and the average forecast inconsistency Δ_i for each group $i = P, D$ as well as the difference thereof, which captures the average treatment effect. The last column displays the p-value of the t-test that this difference $\Delta_D - \Delta_P$ is positive, under the null hypothesis that it is zero (assuming equal variances).

For every quarter of the experiment, the average treatment effect is positive. In 7 out of 12 quarters, it is significantly so at the 95 percent level. The pooled sample tells us that the discrepancy between point forecasts and subjective midpoints is on average positive and significantly higher by 0.18 percentage point of inflation for the D group than for the P group.[11] Clearly, imposing an alternative

[11] To put these numbers into perspective: In a historical and international comparison, Switzerland has low inflation (and interest) rates. The Swiss National Bank's primary goal is to ensure price stability and, as mentioned above, it defines price stability as a consumer price index (CPI) rate less than 2 percent per year and non-negative. Between January 1995 and September 2017, Swiss CPI

Table 3. Forecast Inconsistencies and Treatment Effect

Quarter	Obs.		Inconsistency		Treatment Effect	
	N_D	N_P	Δ_D	Δ_P	$\Delta_D - \Delta_P$	p-value
2014:Q4	56	61	0.26	0.10	0.16	0.04
2015:Q1	57	59	0.19	0.10	0.09	0.20
2015:Q2	50	55	0.35	–0.03	0.38	0.00
2015:Q3	52	49	0.30	0.20	0.10	0.15
2015:Q4	57	57	0.28	0.00	0.28	0.00
2016:Q1	51	57	0.13	0.08	0.05	0.29
2016:Q2	54	51	0.22	–0.02	0.24	0.00
2016:Q3	52	50	0.22	0.12	0.10	0.21
2016:Q4	48	51	0.16	0.10	0.06	0.21
2017:Q1	55	51	0.25	0.10	0.15	0.04
2017:Q2	49	45	0.30	0.10	0.20	0.03
2017:Q3	50	51	0.39	0.07	0.32	0.00
Pooled	631	637	0.26	0.08	0.18	0.00

Note: The table displays, for each quarter of the experiment, the number of respondents N_i and the average inconsistency Δ_i for each group $i = P, D$ as well as the difference thereof. The last column displays the p-value of the t-test that this difference $\Delta_D - \Delta_P$ is positive, under the null hypothesis that it is zero (assuming equal variances). The last row considers the pooled sample.

ordering by asking a density forecast before a point forecast causes forecast inconsistencies to widen significantly.

Thus, the results from the parametric approach confirm those of the non-parametric one by pointing towards the presence of question effects in surveys about inflation expectations. In particular, we find that asking for the density forecast before the point forecast results almost systematically in a statistically significant discrepancy between point forecasts and midpoints, with point forecasts overstating the level of inflation suggested by the density forecast. By contrast, asking for the point forecast first appears to produce

year-on-year inflation was on average 0.5 percent with a standard deviation of 0.9 percent. Between January 2012 and September 2017 (sample covered in this paper), Swiss CPI year-on-year inflation was on average –0.37 percent with a standard deviation of 0.55 percent. In view of the low inflation environment in Switzerland, the average treatment effect shown in Table 3 seems to be significant also from an economic perspective.

differences between midpoints and point forecasts that are of no statistical significance.[12]

All in all, we find marked evidence that question ordering distorts the internal consistency of two-year-ahead inflation forecasts: Question ordering not only affects the *amount* of inconsistencies, it also influences the *direction* in which the mismatch occurs. If question ordering affects consistency, is there anything to say about forecast accuracy? The next section sheds some light on this question.

4. Forecast Accuracy

We so far concentrated on the potentially distortionary effects of question ordering on consistency and saw that the answers to the density forecast question seemed to be less affected by question ordering than the answers to the point forecast question. Notwithstanding, and as far as policymakers are concerned, forecast *accuracy* matters when it comes to policymaking. Since central banks use inflation forecasts as intermediary targets, robustness and accuracy of their forecasts are desirable features.[13] Thus, robustness and accuracy of survey-based inflation expectations either serving as an input variable in forecasting inflation or serving as a forecast themselves should be a plus. A (potential) constant bias is either captured by the regression's intercept when estimated in levels or disappears in a regression when estimated in first differences. On the contrary, if answers are not robust over time due to, e.g., question effects, forecasting with such answers encompasses more uncertainty and might be misleading. However, even though we observed that the answers to the density forecast question seemed to be less affected by question ordering, it is not a priori certain if these answers forecast inflation more accurately than the answers to the point forecast do.

[12] In Section A.3 of the appendix we investigate the relationship between consistency and firm characteristics, such as the size of the firm or the economic sector. We find that characteristics such as uncertainty, firm size, and economic sector seem to play a role too: bigger firms from the service sector tend to be more consistent, and higher uncertainty is associated with more inconsistencies.

[13] For an early argument on the use of forecasts in policymaking, see Svensson (1997). For the theoretical limitations of such use, see Bernanke and Woodford (1997).

To test for forecast accuracy, we focus on the point forecasts and subjective midpoints of the density forecasts; thus we focus on our parametric assessment. As laid out in Section 2, the questions we cover ask about annual inflation in two years' time and the survey is conducted in March, June, September, and December. We therefore take as a reference value for realized inflation π the 24-month-ahead year-on-year change of the Swiss consumer price index (CPI) in the respective month:

$$\pi^m_{t+24} = \frac{CPI^m_{t+24} - CPI^m_{t+12}}{CPI^m_{t+12}}, \tag{1}$$

where m represents March, June, September, December and t is time.[14]

Looking at Figure 2, we observe that both point forecasts and subjective midpoints overestimated inflation until the beginning of 2015 and were more aligned thereafter. The average point forecast of the D group is somewhat persistently higher than that of the P group. For the average midpoint, one can barely distinguish the two series.

As is standard in the forecast literature, we follow Diebold and Mariano (2002, hereafter DM) in order to determine which forecast is more accurate. Key to this approach is its account for serial correlation in the long-run variance (as opposed to regular t-tests).[15]

This leaves us with four different forecasts (two types of questions, i.e., point forecast (PF) or density forecast (DF), and two groups, i.e., point forecast first (P) or density forecast first (D), and six unique pairwise comparisons. Table 4 shows the test results. Each entry displays the column forecast mean squared error (MSE) minus the row forecast MSE. (i, j) denotes forecast $i = PF, DF$ made by group $j = P, D$. A positive value reflects a relatively higher prediction error of the column forecast, and hence, higher accuracy of the row forecast.

[14] The question is formulated in a rather vague manner regarding realized inflation. We therefore also performed our calculations with different measures of realized inflation such as, e.g., year-on-year change of quarterly averages of the CPI in two years' time. Our results on accuracy remained robust to these changes.

[15] Appendix Section A.5 provides methodological details about DM tests.

Table 4. Diebold-Mariano Tests for Predictive Accuracy

Median Forecast				
	(PF,P)	(PF,D)	(DF,P)	(DF,D)
(PF,P)				
(PF,D)	–0.04431			
(DF,P)	0.8875**	0.1331†		
(DF,D)	0.1282**	0.1725*	0.03945*	
Mean Forecast				
	(PF,P)	(PF,D)	(DF,P)	(DF,D)
(PF,P)				
(PF,D)	–0.05476†			
(DF,P)	0.0378*	0.09205†		
(DF,D)	0.08258	0.1195†	0.02749	

Note: $^\dagger p < 0.10$, $^*p < 0.05$, $^{**}p < 0.01$. Entries show the column forecast MSE minus the row forecast MSE. (i, j) denotes forecast $i = PF, DF$ made by group $j = P, D$. Positive values imply higher accuracy of the row forecast.

The top panel of Table 4 shows median forecasts, while the bottom panel displays results for mean forecasts. If we compare (DF,.) with (PF,.) we observe that the subjective midpoint forecast is always more accurate than the point forecast, no matter whether the point forecast was asked first or second. Furthermore, comparing (PF,D) with (PF,P) and (DF,D) with (DF,P) indicates that to each question being asked first, the corresponding forecast yields higher accuracy.

From the analysis above, we know that point forecasts and density forecasts are closer to each other or more consistent when the point forecast is asked first. Moreover, asking for the point forecast first makes the point forecast slightly more accurate ((PF,D) versus (PF,P) in Table 4). However, again from Table 4, density forecasts are also more accurate when being asked first. This points towards the following trade-off: consistency of both forecasts together comes at the cost of subjective midpoint accuracy. Notwithstanding, Table 4 median and mean entries also show us that the gain of asking for density forecasts first rather than second lies between 0.027 and 0.039 in MSE terms ((DF,D) and (DF,P) entries)), while that of asking for point forecasts first rather than second lies between 0.044 and 0.055 in MSE terms ((PF,D) and (PF,P) entries). Thus, asking for the point forecast first not only improves consistency, but also yields the higher benefits in MSE terms. Furthermore, and as already noted, Table 4 shows that density forecasts are still more accurate when being asked second than point forecasts when being asked first or second (see MSE of (DF,.) and (PF,.)).

Existing surveys come in different ways. The Federal Reserve Bank of Philadelphia Survey of Professional Forecasters (US-SPF) or the ECB Survey of Professional Forecasters (ECB-SPF) include both types of questions but present them to the respondents in different ways. While the US-SPF presents the point and subsequently the density forecast on different pages of the survey, the ECB-SPF asks both types of questions on the same page. Results of these answers are, e.g., used in forecasting and modeling: Ang, Bekaert, and Wei (2007), for instance, show that surveys are successful in forecasting inflation. They use, among other measures, inflation expectations of the US-SPF. Grishchenko, Mouabbi, and Renne (2019) include point and density forecasts of the US-SPF and density forecasts of the ECB-SPF when constructing inflation expectations, inflation uncertainty, and inflation-anchoring measures for the United States and the euro area. Our insights might be of practical relevance when designing new surveys or using existing ones. Some awareness of possible question effects might be indicated. Our findings suggest that the answers to the density forecast question seem to be less affected by question ordering than the answers to the point forecast question. In addition, in terms of forecast accuracy, the density forecasts seem to outperform the point forecasts. When both questions are being asked, our results indicate that one should ask for the point forecast first.

5. Discussion

Are our results in line with the literature on question effects we laid out in Section 1? Note, all surveys being analyzed so far had the same ordering: point forecast first, density forecast second. In line with this literature we find that forecast inconsistencies persistently occur. The literature on forecast inconsistencies also finds that point forecasts tend to underestimate inflation with respect to their density forecast. Our findings regarding underestimation for the ordering point forecast first, density forecasts second are mixed. Our results of the non-parametric approach tend slightly towards underestimation, while our results of the parametric approach tend slightly towards overestimation.

Our contribution to this literature lies in the additional insight question ordering brings to the debate. When we switch the order of the questions, i.e., when the question about the density forecast precedes the question about the point forecast, we detect a clear overestimation both for the non-parametric and for the parametric approach. We observe that mainly the answers to the point forecast were affected by the switch in the order, while the answers to the density forecasts remained rather unaffected.

As mentioned in Section 2, our respondents are allowed to go back and forth when answering the questions. In addition, respondents can be in the sample repeatedly. Although the panel of participating CFOs changes over time, as also mentioned in Section 2, and there are 10 to 30 newcomers each quarter, we do not know how many and which CFOs repeatedly participated in the survey. We cannot track the number of "treatments" received by a given CFO, nor the length of the treatments. Some firms might have been presented repeatedly the density question first, while others might have been asked for the point forecast first. Others might have been switching constantly between the two questions. The data at hand do not allow us to exploit any possible panel structure.

One may be worried that the treatment effect weakens over time due to some learning process; see, e.g., Kim and Binder (2020).[16] This could indeed be the case. If some respondents edit their previous answers to improve the consistency of their answers, and if some respondents already know that both types of questions will be asked, this should work against our findings, since it should translate into fewer inconsistencies. Our average treatment effects estimates could therefore be interpreted as lower bounds on forecast inconsistency.

[16] Potential misspecifications arise in particular once we pool our panel data without properly accounting for individual-specific effects, which we however cannot observe. The inclusion of time fixed effects and clustered standard errors at the pseudo-individual level in the regressions in Sections A.3 and A.6.3 of the appendix control—however, only partly—for this potential issue.

Despite the fact that there are newcomers each quarter in the panel of participating CFOs and the order of the two questions was completely randomized with no manual interference, giving each respondent a true 50 percent chance of seeing the question asking for the point forecast before the question asking for the density forecast or the other way around on their computer screen, as time goes by, the expected number of "treatments" received should increase in the sample. A time trend could be a natural, albeit also imperfect proxy for a weakening of the treatment effects. Yet, we could not observe such a trend in our data.[17]

What is known as rounding or heaping at round numbers (see, e.g., Manski and Molinari 2010) could possibly influence our reported amount of inconsistencies. If it does, the observed amount could either increase or decrease. However, Gideon, Helppie-McFall, and Hsu (2017) show that patterns of rounding are not driven by question order in the context of financial questions. It is the difficulty of the question that affects rounding behavior. The response rate to both questions in detail described in Appendix Section A.1 does not give an indication that this is an issue—non-responses to the density forecast occurred, for example, equally often as those to the point forecast.

Could some form of anchoring be at play? One may argue that for a respondent who first sees the question about the density forecast, the point estimate will likely be anchored to the range that was shown in the density question. If anchoring is at play, we would expect the following for those who see the question about the density forecast first: (i) a lower variance of the point forecasts and (ii) a distribution of the point forecasts centered around zero due to the symmetry of the bins. It appears that the latter hypothesis can be discarded by looking at Table 2. The mean point forecasts of the D group are further away from zero than those of the P group. The former hypothesis seems to apply to a certain extent. The point estimates from respondents who see the question about the density forecast first have an overall standard deviation of 0.04 lower (in terms of inflation) than the other group. However, this difference is not statistically significant.[18] As far as the data can tell, anchoring

[17] See, e.g., Figure 2 and Table 3.

[18] Actually, the null hypothesis of equal variance cannot be rejected in any single quarter.

did not cause the point estimates to be more narrowly distributed. Of course, to study the effects of anchoring thoroughly, we would have to run further treatments. However, this goes beyond the scope of this paper and the data at hand do not allow us to draw further conclusions.

All in all, we find evidence that question ordering distorts the internal consistency of two-year-ahead inflation forecasts: Question ordering not only affects the *amount* of inconsistencies, it also influences the *direction* in which the mismatch occurs. But again, we only tested along the dimension of question ordering: With respect to question ordering, we found the answers to the density forecast question to be less sensitive than the ones to the point forecasts question. In terms of forecast accuracy, the answers to the density forecast question outperformed the answers to the point forecast question.

6. Conclusions

We showed that question ordering matters in economic surveys and is relevant for questions on inflation expectations. While the answers to the point forecast question were sensitive to the order in the survey, the answers to the density forecast question were basically unaffected. We found that inconsistencies between the point forecasts and measures of central tendency derived from density forecasts are sizable in the data and are increased if respondents see the question about the density forecast before the one about the point forecast. In terms of forecast accuracy, the answers to the density forecasts seem to outperform the answers to the point forecasts.

These results suggest that the design of surveys also matters in regard to economics. When gauging expectations on macroeconomic variables from surveys, policymakers and market participants alike should be aware that biases due to question effects might be at play. This should not imply that surveys are not a useful policy instrument; on the contrary, they deliver additional information compared to market data, or sometimes cover areas where no market data exist.

Appendix

A.1 Data

We compile our data by assembling Deloitte's quarterly surveys into a larger data set. Because we focus on forecast inconsistencies, we drop all observations for which either the point forecast or the density forecast on inflation expectations is missing (the survey does not force the box to be filled in). This occurred 246 times out of 1,514 for the experiment sample, and 129 out of 1,251 for the pre-experiment one. The number of respondents who answered neither question was 286 (of which 202 were from the experiment sample); 48 respondents (of which 24 were from the experiment sample) answered only the density forecast question; and 41 (of which 20 were from the experiment sample) answered only the point forecast question. A missing density forecast occurs when none of the intervals is used. When at least one interval contains a positive probability, we interpret unused intervals as zero-probability intervals.

Furthermore, the probabilities assigned to the intervals occasionally do not add up to a 100 percent (the survey does not require answers to do so). For 93.5 percent of all observations, however, the probabilities add up to 100 percent. For 97.7 percent of them, their sum is comprised between 90 and 110 or is equal to one. All the remaining observations range between 0.3 and 500. Nevertheless, to conserve the full information of our sample, we normalize all the probabilities so that they add up to 100 percent.

In addition to inflation expectations, the questionnaire provides information on the responding firm. In particular, three questions allow us to know more about the size, the openness, and the sector of the firm:

3. What was your company's turnover in the last financial year?
4. How much of your company's revenues are earned outside Switzerland?
5. In which sector does your company primarily operate?

Question 3 offers several intervals that we group into two categories: less than CHF 500 million (*low* turnover), and CHF 500 million or more (*high* turnover). Question 4 answers are regrouped as follows: less than one-third (*low* share), and one-third or more (*high* share). Question 5 suggests a list of several "sectors" from which respondents are allowed to select more than one answer. We group all combinations into three sectors: construction, manufacturing, and services.[19]

Table A.1 shows the summary statistics of the data we analyze. It shows the number of observations that were first assigned the point—respectively, the density—forecast and their respective sample mean. It also gives an overview of the average assigned probability for each bin of the density forecast. In addition, it reports details regarding the turnover, openness, and sector of the firms. The statistical analysis of the differences between the group that was first asked a density forecast and the group that was first asked a point forecast and of their forecast inconsistencies is the subject of the following section.

A.2 Visual Parametric Approach

In a next step, we analyze the differences between point forecasts and subjective midpoints within each group, i.e., the so-called forecast inconsistencies. The panels on the left of Figure A.1 plot as a time series the quarterly averages of point forecasts (blue dashed lines) and subjective midpoints (green dashed lines), as well as the differences between the two (i.e., the forecast inconsistencies, red dotted lines) respectively for the pre-experiment sample (top panels) and the experiment sample broken down by question ordering (middle and bottom panels).[20] The red dashed lines surrounding the series of mean forecast inconsistencies are the lower and upper bounds of the 95 percent confidence interval (CI) for the difference between

[19]The groups are constructed to match the statistical classification of economic activities in the European Community (NACE) at best.

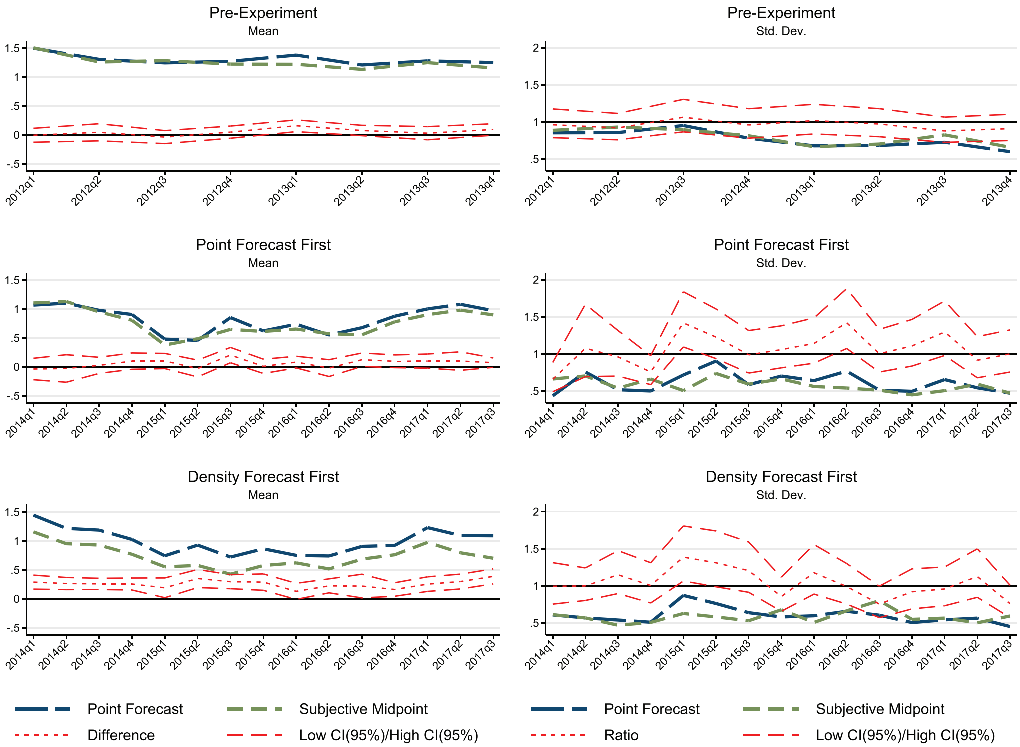
[20]Note that Figure A.1 also shows the trial period of the experiment (2014:Q1–2014:Q3) for each group, although, as we argued before, it does not provide a reliable assessment of the treatment effect. All the comments exposed here therefore do *not* consider this period, despite the robustness in doing so.

Table A.1. Deloitte CFO Survey Summary Statistics

Variable	Observations			Mean			Std. Dev.		
	N	N_D	N_P	μ	μ_D	μ_P	σ	σ_D	σ_P
Inflation Expectations									
Point Forecast	**1,268**	**631**	**637**	0.84	0.92	0.76	0.65	0.63	0.67
Two-years-ahead inflation expectation									
Density Forecast	**1,268**	**631**	**637**						
Probability that two-years-ahead inflation lie within. . .									
(−∞, −4]				0.09	0.11	0.07	0.96	1.29	0.46
(−4, −2]				0.54	0.45	0.64	2.25	1.59	2.75
(−2, −1]				3.33	3.46	3.19	8.15	8.67	7.60
(−1, 0]				16.83	17.49	16.19	17.33	18.28	16.33
(0, 1]				47.41	47.27	47.54	24.71	24.95	24.49
(1, 2]				25.09	24.37	25.82	20.98	20.82	21.12
(2, 4]				6.04	6.14	5.93	9.61	10.02	9.18
(4, +∞)				0.66	0.71	0.62	3.73	4.46	2.85
Attributes									
Turnover	**1,255**	**625**	**630**						
For the last financial year (millions CHF)									
[0, 50)	240	129	111						
(50, 100]	191	86	105						
(100, 500]	378	180	198						
(500, 1000]	148	74	74						
(1000, +∞)	298	156	142						
Openness	**1,222**	**616**	**606**						
Share of revenues earned abroad									
[0, 1/3)	517	256	261						
[1/3, 2/3)	118	56	62						
[2/3, 1]	587	304	283						
Sector	**1,256**	**624**	**632**						
Construction	103	56	47						
Manufacturing	590	294	296						
Services	563	274	289						

Note: Each cell represents the number of observations (N_i), the sample mean (μ_i), or the sample standard deviation σ_i from group $i = P, D$ for the sample between 2014:Q4 and 2017:Q3, i.e., during the experiment. P (D) denotes the respondents who were asked for a point (density) forecast first.

Figure A.1. The Effect of Question Ordering on Forecast Inconsistencies



Note: Left panels plot quarterly averages of point forecasts and subjective midpoints, as well as their differences together with the 95 percent CI bands thereof assuming equal variances. Right panels plot quarterly standard deviations of the same variables, as well as their ratio together with the 95 percent CI bands thereof. Each row considers a different subsample: pre-experiment (2012:Q1–2013:Q4) and experiment (2014:Q1–2017:Q3) by question ordering.

the mean of point forecasts and the mean of subjective midpoints, computed separately for each quarter through two-sample mean-comparison t-tests assuming equal variances. In a very similar fashion, the right panels show the quarterly standard deviations of point forecasts and subjective midpoints as well as their ratios. The dashed lines surrounding these ratios are the bounds of the 95 percent CI thereof, computed separately for each quarter through two-sample variance-comparison F-tests.

Focusing first on the left panels of Figure A.1 allows us to assess the effect of question ordering on forecast consistency. A quick comparison between the top and middle panels tells us that the P group indeed follows the pattern of the pre-experiment sample. In fact, similar to prior to the experiment, those who submitted a point forecast first during the experiment provided on average point forecasts sometimes higher, sometimes lower than their respective midpoints, but for a difference that can almost never be considered significantly different from zero.

By contrast, forecasters from the D group systematically submitted point forecasts that were higher on average than their subjective midpoints. Strikingly, this overstatement of inflation made by point forecasts relative to density forecasts is statistically significant at the quarterly level for almost every period. We thus observe a strong treatment effect: switching the order by asking for the density forecast before the point forecast exerts an upward pressure on point forecasts relative to midpoints, thereby producing an increase in forecast inconsistencies.

Finally, looking at the right panels of Figure A.1 provides an indication of the plausibility of our results. The standard deviation of point forecasts (or subjective midpoints) is a measure of *disagreement* and is often used in the literature as a proxy for general uncertainty.[21] We interpret the quasi-permanent conservation of the null hypothesis (i.e., that standard deviations are equal) for both question orderings as evidence that question ordering affects the amount of inconsistencies, but not the general level of disagreement among forecasters. In other words, asking for a density forecast first intensifies the discrepancies between point forecasts and midpoints, but does so without distorting their respective dispersion. We can thus exclude that the experiment itself came as a surprise, which would in turn drive our results.

[21]Because the quarterly sample size of each question ordering is half the size of the pre-experiment sample, the volatility of the series becomes mechanically lower.

Table A.2. Recoding Attributes in Binary Variables

Variable	Observations		
	N	N_D	N_P
Attributes			
Turnover	**1,255**	**625**	**630**
For the last financial year (millions CHF)			
$0 = [0, 500)$	809	395	414
$1 = [500, +\infty)$	446	230	216
Openness	**1,222**	**616**	**606**
Share of revenues earned abroad			
$1 = [0, 1/3)$	517	256	261
$0 = [1/3, 1]$	705	360	345
Sector	**1,256**	**624**	**632**
0 = Construction & Manufacturing	693	350	343
1 = Services	563	274	289

Note: The table displays the number of observations for each attribute after recoding them into binary variables. For the original data, see Table A.1.

A.3 Regression Analysis

What drives forecast inconsistencies? As we have already noted, question ordering does. However, other factors such as firm characteristics or uncertainty might very well be influencing the discrepancy between density forecasts and point forecasts. To address this question, we make use of the firm's attributes present in our data, define a measure of uncertainty, and estimate two models: a logistic regression and a linear regression.

Recall that we have information about the turnover, the share of revenues earned abroad, and the operating sector of the respondent's firm. To be parsimonious, we recode these three attributes into binary variables. For each of them, Table A.2 displays the threshold we chose as well as the number of observations falling in each category by question ordering. Note that neither group is over- or underrepresented in terms of their question ordering, so that we can exclude that attrition is correlated with the attributes.[22]

We coded the dummy variables so that we expect the value 1 to be associated with more consistency. First, we consider a turnover greater than or equal to CHF 500 million to be a high turnover. A higher turnover should reflect a higher size and access to better data, or a greater need for quality forecasts. Second, we define a share of revenues earned abroad between zero and one-third as low openness. Arguably, a domestically oriented firm is more likely to depend on national rather than international prospects, and thus to monitor local prices accurately. Finally, firms from the services sector could be associated with higher levels of technology or financial market knowledge, and thus with more rigorous forecasts.

As a measure of uncertainty at the individual level, we argue as Clements (2010) that the number of bins that are assigned a positive probability by the respondent is a good proxy for the variance of the density function underlying forecasters' expectations over future inflation. The advantage of this measure is that it is nonparametric and readily available.[23] Similarly, we recode this variable as a dummy whose value is 1 if the number of bins used by the respondent is lower than or equal to 3 (i.e., if the forecast is of high certainty) and 0 otherwise.

We turn now to our baseline model, the logistic regression (logit). In this respect, suppose we have N independent realizations $\{y_j\}_{j=1}^{N}$ of a random variable Y_j. Let $Y_j \sim \text{Bernoulli}(\lambda_j^c)$ and y_j be equal to 1 if respondent j is consistent and 0 otherwise. We can then model the probability λ_j^c using a linear predictor function according to

$$\text{logit}(\lambda_j^c) = d_j\alpha + x_j'\beta + z_j\gamma, \tag{A.1}$$

where d_j is a dummy for the treatment group, x_j a vector of attributes, z_j a measure of uncertainty, and α, β, γ a set of parameters. We then estimate the regression coefficients in Equation (A.1) through maximum likelihood estimation.

[22]Table A.10 in Section A.8 explores the correlations between firm attributes. There is little correlation present in the data.

[23]Appendix Section A.6 explores the robustness of our results to using parametric evaluations of subjective dispersion.

This specification makes use of our non-parametric assessment of consistency. The idea here is to predict the likelihood that a forecaster will produce a consistent forecast based on his or her question ordering, the characteristics of his or her employing firm, and the uncertainty surrounding his or her forecast. However, since the coefficients that Equation (A.1) yields are log odds and thereby difficult to interpret, we compute and report the marginal probability changes evaluated at means associated with a discrete change away from the reference category. Because we coded our binary regressors such that switching away from the reference category (i.e., from zero to one) should increase the probability of being consistent, our estimates will tell us by how much it does at the margin for an average respondent.[24]

As an alternative model, we use our parametric assessment of consistency and estimate the following linear regression (LR):

$$-|\Delta_j| = d_j\tilde{\alpha} + x_j'\tilde{\beta} + z_j\tilde{\gamma} + \tilde{\varepsilon}_j, \tag{A.2}$$

where $|\Delta_j|$ is the absolute difference between the point forecast and the midpoint given by respondent j, $\tilde{\alpha}$, $\tilde{\beta}$, $\tilde{\gamma}$ a new set of parameters, and $\tilde{\varepsilon}_j$ are i.i.d. errors.

Considering the distance in absolute terms and negating it makes our two specifications comparable, because it recovers our notion of consistency in levels. In particular, all else equal, each coefficient can be interpreted as the average marginal increase in closeness between subjective midpoints and point forecasts produced by switching away from the reference category of the dummy regressors. While Equation (A.1) provides estimates to be interpreted in terms of probabilities, Equation (A.2) yields estimates in terms of percentage points of inflation. Therefore, the linear regression model will serve us both as an assessment of the robustness of the results under the logit and as an indication of their economic significance.

Table A.3 displays the results from our two specifications based either on midpoint consistency (columns 1 and 2) or on median

[24] Recall that the logistic transform is a non-linear combination of the regressors, so that we need to fix their value to assess marginal probability changes. We take their sample respective means.

Table A.3. Logit and LR of Midpoint and Median Consistency on Attributes

	Subjective Midpoint		**Subjective Median**	
	Logit (1)	**LR (2)**	**Logit (3)**	**LR (4)**
Point Forecast First	0.0635**	0.0716**	0.0285	0.102**
	(2.82)	(3.96)	(1.06)	(4.36)
High Certainty	0.0723**	0.0513	0.103***	0.0726**
	(3.21)	(1.84)	(5.54)	(3.24)
High Turnover	0.0668***	0.0560***	0.0333	0.0439**
	(3.69)	(4.61)	(1.27)	(3.34)
Low Openness	0.00959	0.00818	0.00964	0.0438*
	(0.40)	(0.37)	(0.55)	(2.62)
Services Sector	0.0352*	0.0416	–0.0194	–0.00636
	(2.06)	(1.54)	(–1.00)	(–0.36)
Constant		–0.502***		–0.597***
		(–19.95)		(–22.63)

Note: t-statistics in parentheses. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. $N = 1,217$. Logistic regression (logit) models use the proportion of consistent forecasts as the dependent variable, whereas linear regression (LR) models use the negative absolute difference between the point forecast and the central tendency measure derived from the density forecast. Logit coefficients represent marginal probability changes evaluated at means. All models include time fixed effects, and standard errors are clustered at the quarterly level.

consistency (columns 3 and 4). Note that to account for potential global time-varying factors, we include in all our models time fixed effects.[25,26] As mentioned above, the logit coefficients (odd columns) show the marginal increase in the probability of being consistent

[25] A caveat of our approach, however, is that we cannot control for individual fixed effects. This is not a problem insofar as forecasters' ability to be consistent through time is *not* correlated with our regressors. In other words, we need to make the assumption that this ability is unobservable by employers and that there is no self-selection of better forecasters into certain types of firms. Since this may be argued to be a somewhat strong assumption, one should interpret our estimates as upper bounds.

[26] All our results are robust to the non-inclusion of time fixed effects.

induced by a discrete change of the variable in row, when all the other variables take their mean value. LR coefficients (even columns) express the average percentage-point increase in closeness between the center of the density forecast and the point forecast associated with the same change. Standard errors are clustered at the quarterly level.[27]

Overall, the results confirm our previous findings that question ordering matters. Focusing on subjective midpoints first, column 1 indicates that an average forecaster (in terms of its other characteristics) is as much as 6.35 percent more likely to submit a consistent forecast if he or she is asked for a point forecast first. Column 2 tells us that such ordering makes the point forecast on average closer to the subjective midpoint by 7.16 basis points.[28]

In addition, Table A.3 suggests that consistency depends on some firm attributes and certainty as well. First, being more certain induces a marginal increase of 7.23 percent in the probability of being consistent. However, it does not seem to exert a significant effect on the closeness between subjective midpoints and point forecasts. Second, if the respondent works in a firm with a high turnover, the probability marginally increases by 6.68 percent, and reduces the distance between the midpoint and the point forecast by 5.6 basis points. Third, we cannot say that openness has an impact on consistency in either specification. Fourth, although consistency in levels does not seem to significantly vary with the sector in which the firm operates (column 2), it appears that switching to the service industry marginally increases the probability for the average forecaster to be consistent by 3.52 percentage points. Finally, the constant reflects part of our previous results, saying that a rather uncertain forecaster working in a small open construction or manufacturing firm hands in a point forecast on average 0.5 percentage point away from the midpoint if he or she sees the question about the density forecast first.

[27]In Section A.6, we construct pseudo-identifiers based on the combination of firms' turnover, openness, and sector, and we cluster standard errors at this level to account for heteroskedasticity. Our results are robust.

[28]A basis point is a hundredth of a percent of inflation.

We now inspect median consistency to assess the robustness of these results. The logistic regression in this context (column 3) globally suggest a similar picture but with somewhat less statistical significance. In fact, only certainty turns out to significantly raise the probability of consistency. Moreover, the service-sector dummy now exerts a negative marginal effect—although not significant—on such probability. Column 4 on the other hand reveals that the linear regression model performs better than its counterpart from column 2. We can indeed infer that all our dummy variables except for the sectoral one provokes a positive and significant effect on forecast consistency as measured by the closeness between subjective point forecasts and the median of the density forecasts.

Interestingly, the positive effect on consistency of question ordering and certainty is of higher magnitude than in column 2. This result together with the non-significance of the corresponding coefficient in column 3 indicates that question ordering makes little difference in the marginal probability that the misalignment between the median and the point forecast exceeds a relevant threshold but stills makes this misalignment on average greater by 10.2 basis points when the density forecast is asked first. In addition, the constant term reveals a greater discrepancy than in column 2. This reinforces our previous argument that subjective midpoints capture the information relevant to point forecasts better than medians.

A.4 Distribution Fitting

As mentioned in Section 3, assuming that all the mass of the density forecast lies at the center of each bin tends to overstate the level of uncertainty if the underlying distribution is thought to be bell-shaped. Although we do not make explicit use of the second moment of the density forecasts, it is worth considering an alternative parametric approach to assess the robustness of our results.

Thus, following Giordani and Söderlind (2003), we can assume that each forecaster's density forecast is normally distributed, and we can solve for each individual parameter through numerical optimization. Formally, we would like to estimate for each respondent

$j \in \{1, \dots, N\}$ the subjective mean μ_j and the subjective variance σ_j^2 according to

$$\min_{\hat{\mu}_j, \hat{\sigma}_j^2} \sum_{k=1}^{K} (P[L_k < Z_j \leq U_k] - p_{j,k})^2,$$

where K is the number of bins, $Z_j \sim \mathcal{N}(\mu_j, \sigma_j^2)$; L_k and U_k respectively denote the lower and upper bound of bin k; and $p_{j,k}$ denotes the probability associated by respondent j to bin k. In other words, we pick the set of parameters that minimizes the sum of squared differences between the probability mass lying under the curve of a normal density following these parameters, and the probability mass assigned by the respondent.

When the number of bins used by the respondent does not exceed two, the fitting may not be satisfying. To address this issue in a simple manner we assume (i) a uniform distribution within the bin if only one bin is used, and (ii) that the mass lies at the center of the bin if exactly two bins are used. The first assumption avoids a subjective variance of 0. Note that this procedure slightly differs from the one used by Giordani and Söderlind (2003) since we have to address bins of different sizes. However, these two special cases occur in less than 20 percent of our experiment sample, and thus should not be of critical importance.

Overall, this specification is somewhat more restrictive than the one we use in the paper, as it assumes that the underlying distribution is symmetric and unimodal. Nevertheless, it is appealing in that it equates the mean, the mode, and the median. Appendix Section A.6 shows the results associated with this approach.

A.5 Diebold-Mariano Tests

Suppose we have two competing forecasts $\{\hat{x}_{it}\}_{t=1}^{T}$ and $\{\hat{x}_{jt}\}_{t=1}^{T}$ of the same time series $\{x_t\}_{t=1}^{T}$, with respective resulting forecast errors $\{\hat{e}_{it}\}_{t=1}^{T}$ and $\{\hat{e}_{jt}\}_{t=1}^{T}$. Let $g(x_t, \hat{x}_{kt}) = g(\hat{e}_{kt})$ be an arbitrary loss function of the realization and the prediction $k = i, j$, or equivalently, the forecast error. We test the null hypothesis of equal predictive accuracy, i.e., whether the expected loss differential is zero, $E[d_t] \equiv E[g(e_{it}) - g(e_{jt})] = 0$.

Under stationarity and short memory of the loss differential series $\{d_t\}_{t=1}^{T}$, Diebold and Mariano (2002) propose the following test statistic:

$$S = \frac{\bar{d}}{\sqrt{\frac{2\pi \hat{f}_d(0)}{T}}} \overset{a}{\sim} N(0,1),$$

where $\bar{d}$ is the sample mean loss differential, and $\hat{f}_d(0)$ is a consistent estimate of the spectral density of the loss differential at frequency 0.[29,30]

Typical criteria for the loss function $g(\cdot)$ include mean squared error (MSE), mean average error (MAE), and mean average percentage error (MAPE). Following, we make use of the MSE, $g(\hat{e}_{kt}) = \hat{e}_{kt}^2$.[31]

Note that the DM test compares *one* prediction per competing forecast for each observed period, so we have to summarize our data along the panel dimension. To that end, the two most natural statistics are the mean and the median. This leaves us with four different forecasts (two types of questions, i.e., point forecast (PF) or density forecast (DF), and two groups, i.e., point forecast first (P) or density forecast first (D), and six unique pairwise comparisons.

A.6 Robustness

A.6.1 Non-Parametric Mode

One could argue that the mode of the density forecast is reported as the point forecast rather than the midpoint or the median. To

[29] Such an estimate requires to choose the maximum order of the lag to consider when computing the long-run variance of the loss differential series from its autocovariance function. Diebold and Mariano (2002) suggest $k-1$, where k is the forecast horizon ($k = 8$ quarters in our case). Alternatively, one can use the Schwert criterion, which is $12 * (T/100)^{1/4}$ and which yields something between 7 and 8. We select 7, consistent with both criteria. Furthermore, to ensure non-negativity of the estimate of the spectral density, we use a Bartlett kernel.

[30] As noted by Harvey, Leybourne, and Newbold (1997), with few time-series observations and long-horizon forecasts, test size distortions likely exist. Table A.8 shows the DM tests with bootstrapped standard errors.

[31] Our results are robust to these different criteria.

Table A.4. Mode Consistency by Question Ordering

Quarter	Subjective Mode					
	Consistent		Below		Above	
	λ_P^c	λ_D^c	λ_P^b	λ_D^b	λ_P^a	λ_D^a
2014:Q4	73.8	73.2	16.4	3.6	9.8	23.2
2015:Q1	74.6	75.4	18.6	12.3	6.8	12.3
2015:Q2	70.9	64.0	20.0	4.0	9.1	32.0
2015:Q3	85.7	73.1	10.2	7.7	4.1	19.2
2015:Q4	77.2	71.9	17.5	7.0	5.3	21.1
2016:Q1	80.7	74.5	14.0	13.7	5.3	11.8
2016:Q2	64.7	64.8	29.4	7.4	5.9	27.8
2016:Q3	82.0	59.6	10.0	13.5	8.0	26.9
2016:Q4	86.3	79.2	9.8	6.3	3.9	14.6
2017:Q1	78.4	65.5	13.7	9.1	7.8	25.5
2017:Q2	73.3	79.6	17.8	8.2	8.9	12.2
2017:Q3	80.4	74.0	11.8	2.0	7.8	24.0
Pooled	77.2	71.2	15.9	7.9	6.9	20.9

Note: See Table 1 for details.

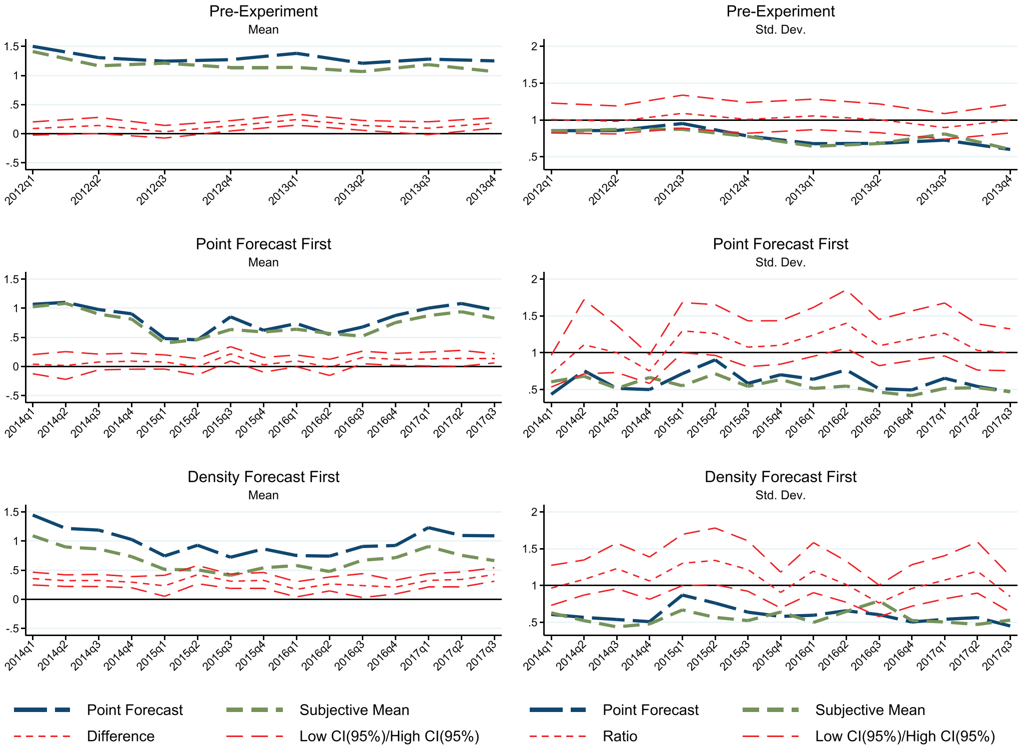
address the plausibility of such a hypothesis, we apply the same non-parametric exercise to this statistic.

The non-parametric subjective mode is taken as the bin itself to which the highest probability is assigned. When the highest probability is assigned to more than one bin, we take the bin that is closest to the midpoint. We do so because it prevents the need to address cases involving bins of different sizes, or cases of multi-modal density forecasts.

For each quarter and by question ordering, Table A.4 displays the proportion of respondents whose point forecast lies respectively within, below, or above its consistency level.

All the conclusions drawn from Table 1 are conserved. Asking for a point forecast first yields point forecasts that are more frequently mode consistent than asking for a density forecast first by a 6 percentage points average margin. Moreover, we observe a stronger

Figure A.2. Treatment Effect Under an Alternative Parametric Approach



Note: See Figure A.1 for details.

discrepancy between the two question orderings in regard to inconsistent forecasts. In particular, an inconsistent point forecast is much more likely to lie below its consistent level if the point forecast is asked first, but much more likely to lie above it if the density forecast is asked first.

A.6.2 Normally Fitted Parameters

Figure A.2 shows the effect of question ordering on forecast inconsistencies when we use the subjective means stemming from the normal

Table A.5. Forecast Inconsistencies and Treatment Effect

Quarter	Obs.		Inconsistency		Treatment Effect	
	N_D	N_P	Δ_D	Δ_P	$\Delta_D - \Delta_P$	p-value
2014:Q4	56	61	0.31	0.09	0.22	0.01
2015:Q1	57	59	0.24	0.09	0.15	0.09
2015:Q2	50	55	0.41	0.01	0.39	0.00
2015:Q3	52	49	0.31	0.22	0.09	0.15
2015:Q4	57	57	0.32	0.04	0.29	0.00
2016:Q1	51	57	0.17	0.10	0.08	0.18
2016:Q2	54	51	0.25	–0.01	0.26	0.00
2016:Q3	52	50	0.24	0.16	0.08	0.25
2016:Q4	48	51	0.21	0.13	0.08	0.16
2017:Q1	55	51	0.33	0.12	0.20	0.01
2017:Q2	49	45	0.34	0.14	0.19	0.02
2017:Q3	50	51	0.42	0.14	0.28	0.00
Pooled	631	637	0.29	0.10	0.19	0.00

Note: See Table 3 for details.

density fitting approach described in Section A.4 of this appendix instead of the subjective midpoints.

Clearly, the picture yields the same general interpretation as to the effect of question ordering on forecast inconsistencies. For the experiment sample, although we observe a slightly higher degree of inconsistencies for the P group compared to using midpoint (see Figure A.1), these quarterly average inconsistencies remain of rather low statistical significance. By contrast, the null hypothesis of equal means between point forecasts and subjective means can still be rejected for every single quarter regarding the D group. The treatment effect under this specification remains qualitatively unchanged, as indicated by Table A.5. Indeed, with a significant average difference in inconsistencies of 0.19 percentage point of inflation, we reject the null hypothesis that this difference is zero at the quarterly level in 7 out of 12 cases.

Table A.6 displays the results from the linear regression estimated in Equation (A.2) when we use the subjective means from

Table A.6. LR of Subjective Mean Consistency on Attributes

	Subjective Mean	
	(1′)	**(2′)**
Point Forecast First	0.0870***	0.0862***
	(4.68)	(4.93)
High Certainty	0.0425	0.105**
	(1.53)	(3.26)
High Turnover	0.0537**	0.0559**
	(3.94)	(4.41)
Low Openness	0.0230	0.0148
	(1.19)	(0.71)
Services Sector	0.0142	0.0107
	(0.47)	(0.36)
Constant	–0.486***	–0.515***
	(–16.75)	(–17.75)

Note: See Table A.3 for details.

the fitted normal distributions instead of the midpoints in the computation of the dependent variable.

The cells are therefore the coefficients from the linear regression of the absolute difference in negative terms between the point forecasts and the subjective means on question ordering, certainty, and firm characteristics. Column 1′ considers the exact same variable of certainty as in the paper (cf. Table A.3), while column 2′ considers an alternative dummy variable based on the subjective standard deviation derived from the normal fitting approach. Namely, its value is 1 if the subjective standard deviation is less than or equal to 0.6, and 0 otherwise. The value of 0.6 was chosen because it is the median subjective standard deviation in the full sample.

Comparing column 1′ here with its counterpart in Table A.3 (i.e., column 2) leads to the exact same conclusions. Furthermore, looking at column 2′ reinforces the view that more certainty (at the individual level) is associated with a higher degree of consistency. Using a parametric measure of certainty, namely, the subjective standard deviation recoded into a dummy variable, makes the corresponding coefficient highly significant.

Overall, we argue that all our results are robust to adopting the alternative parametric approach described in Section A.4 of the appendix, which consists in fitting normal distributions to individual density forecasts. Using the subjective means instead of the midpoints yields the same general conclusions.

A.6.3 Accounting for (Some) Heteroskedasticity

Arguably, the forecasts (and forecast errors) produced by a given CFO are likely autocorrelated. Thus, one may be worried that the standard errors calculated in the regression analysis (Section A.3 of this appendix) are unreliable due to heteroskedasticity. Ideally, one would like to cluster standard errors at the individual level. But because we do not observe the individual identifiers from our panel data, we cannot.

To circumvent the issue, we generate what we call pseudo-identifiers based on the combination between each firm sector, turnover, and share of revenues earned abroad. In practice, each combination is assigned a unique identifier that likely tracks firms (or groups of firms) along the time dimension. Though they do not uniquely identify firms in the data, they allow to improve on the interpretation of our data as repeated cross-samples. Moreover, firms have unlikely switched categories over the time of our experiment. By clustering standard errors at the pseudo-individual level, we therefore allow for heteroskedasticity at the firm (or group of very similar firms) level.

Table A.7 shows the results of the regression analysis when standards errors are clustered at the pseudo-individual level. Compared to Table A.3, results on question ordering remain robust. In fact, this approach only weakens the significance of some of the controls: Being a firm from the service sector is no longer significant in column 1, more certainty is no longer associated with higher levels of forecast consistency from column 2, and openness does not seem to matter anymore in column 4. Note that controlling for pseudo-individual fixed effects as well yields the same general conclusions.

Table A.7. Logit and LR with Clustered Standard Errors

	Subjective Midpoint		Subjective Median	
	Logit (1)	**LR (2)**	**Logit (3)**	**LR (4)**
Point Forecast First	0.0635**	0.0716**	0.0285	0.102**
	(2.87)	(3.21)	(1.00)	(3.12)
High Certainty	0.0723**	0.0513*	0.103***	0.0726**
	(2.95)	(2.03)	(4.16)	(3.07)
High Turnover	0.0668**	0.0560**	0.0333	0.0439
	(2.72)	(2.70)	(1.08)	(1.84)
Low Openness	0.00959	0.00818	0.00964	0.0438
	(0.38)	(0.35)	(0.28)	(1.74)
Services Sector	0.0352	0.0416	–0.0194	–0.00636
	(1.39)	(1.81)	(–0.58)	(–0.26)
Constant		–0.502***		–0.597***
		(–13.57)		(–13.75)

Note: t statistics in parentheses. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. $N = 1{,}217$. Logistic regression (logit) models user the proportion of consistent forecasts as the dependent variable, whereas linear regression (LR) models use the negative absolute difference between the point forecast and the central tendency measure derived from the density forecast. Logit coefficients represent marginal probability changes evaluated at means. All models include time fixed effects, and standard errors are clustered at the pseudo-individual level. See Appendix Section A.6 for details.

A.6.4 Diebold-Mariano Tests with Bootstrapped Standard Errors

Table A.8 shows the DM tests with bootstrapped standard errors with 1,000 replications. Compared to Table 4, the significance is only slightly affected downwards.

A.7 Treatment Effect in Non-Parametric Approach

In Table 1 we show, by group, the percentage of respondents whose point forecast is respectively consistent with, below and above the central tendency of the corresponding density forecast. For the sake of clarity, the table does not show the significance of the differences between groups. Doing so would amount to assessing the

Table A.8. Diebold-Mariano Tests for Predictive Accuracy

Median Forecast				
	(PF,P)	(PF,D)	(DF,P)	(DF,D)
(PF,P)				
(PF,D)	–0.04431			
(DF,P)	0.08875*	0.1331		
(DF,D)	0.1282*	0.1725*	0.03945*	
Mean Forecast				
	(PF,P)	(PF,D)	(DF,P)	(DF,D)
(PF,P)				
(PF,D)	–0.05476			
(DF,P)	0.03728†	0.09205†		
(DF,D)	0.08258	0.1195†	0.02749	

Note: $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$. Entries show the column forecast MSE minus the row forecast MSE. (i,j) denotes forecast $i = PF,DF$ made by group $j = P,D$. Positive values imply higher accuracy of the row forecast. Significance stars correspond to bootstrapped standard errors with 1,000 replications.

treatment effect of our experiment, which we document in a more sophisticated way through the parametric approach (namely, in Table 3).

Since it still may be of interest, Table A.9 displays the differences between the two groups in the proportions along with the p-value for the corresponding (not shown) t-statistics. The null hypothesis is that the proportion of respondents is the same regardless of the question ordering, and the test assumes equal variance.

As seen in Table A.9, the difference in midpoint consistency ($\Delta\lambda^c$) is statistically significant when one considers the pooled sample (last row). This observation is also true for the difference in mean inconsistencies both for the share of forecasts lying below and for the share of forecasts lying above their consistent level. In other words, respondents who are asked first for a density forecast tend to be less consistent (as opposed to the other group) and when they are inconsistent, they tend to overestimate inflation more and to underestimate it less.

Table A.9. Group Differences in Forecast Consistency

	Subjective Midpoint						Subjective Median					
	Consistent		Below		Above		Consistent		Below		Above	
Quarter	$\Delta\lambda^c$	p	$\Delta\lambda^b$	p	$\Delta\lambda^a$	p	$\Delta\lambda^c$	p	$\Delta\lambda^b$	p	$\Delta\lambda^a$	p
2014:Q4	–1.8	0.80	8.1	0.07	–6.2	0.32	0.7	0.93	13.0	0.01	–13.7	0.06
2015:Q1	14.7	0.07	–2.1	0.71	–12.6	0.07	0.9	0.91	4.7	0.48	–5.6	0.35
2015:Q2	12.5	0.17	6.5	0.30	–19.1	0.01	7.3	0.44	17.8	0.01	–25.1	0.00
2015:Q3	10.6	0.20	0.2	0.95	–10.8	0.16	6.5	0.45	2.4	0.64	–8.9	0.24
2015:Q4	5.3	0.52	15.8	0.00	–21.1	0.00	5.3	0.51	14.0	0.01	–19.3	0.00
2016:Q1	7.3	0.30	2.9	0.57	–10.2	0.06	–1.2	0.88	4.4	0.45	–3.2	0.61
2016:Q2	–5.0	0.53	13.9	0.02	–8.9	0.14	–11.9	0.22	22.0	0.00	–10.1	0.22
2016:Q3	14.8	0.07	0.2	0.96	–15.1	0.04	24.4	0.01	–5.5	0.38	–18.9	0.01
2016:Q4	–0.9	0.91	3.7	0.45	–2.8	0.68	1.2	0.88	1.7	0.70	–2.9	0.69
2017:Q1	4.0	0.62	5.9	0.07	–9.9	0.20	3.7	0.66	8.0	0.08	–11.7	0.13
2017:Q2	–4.0	0.64	6.8	0.14	–2.8	0.72	–6.6	0.48	11.7	0.08	–5.0	0.51
2017:Q3	18.1	0.01	2.0	0.32	–20.0	0.00	10.4	0.23	7.8	0.10	–18.2	0.02
Pooled	6.4	0.01	5.5	0.00	–11.8	0.00	3.4	0.17	8.6	0.00	–12.0	0.00

Note: $\Delta\lambda^k$ is the difference $(\lambda^k_P - \lambda^k_D)$ between the two groups in the proportions shown in Table 1 for each category $k = c, b, a$, that is, whether the point forecast lies within, below, or above its level of consistency. p denotes the p-value for the t-test that this difference is zero, assuming equal variance.

Table A.10. Correlation between Attributes

	High Turnover	High Openness	Service Sector	High Certainty
High Turnover	1			
High Openness	0.04	1		
Service Sector	–0.04	–0.30***	1	
High Certainty	0.02	0.00	–0.00	1

Note: ***$p < 0.001$. Each entry is the pairwise Pearson correlation between the row and the column variable.

In regard to median consistency, it appears that the difference in the pooled sample ($\Delta\lambda^c$) is not significant, although the differences in the distribution of inconsistencies ($\Delta\lambda^b$ and $\Delta\lambda^a$) are. This generally confirms our previous finding that when a point forecast is inconsistent, it is more likely to be above (below) its consistency level if the density forecast was asked first (second).

As for quarterly differences, they are hardly significant. This can be generally explained by the small sample size. Nevertheless, all the figures, when they are significant, offer a consistent view and lead to the same conclusions as above.

A.8 Correlation Between Attributes

Table A.10 displays correlations between firm attributes displayed in Table A.2 together with the significance thereof. As shown in the table, there is little correlation present in the data. In fact, only firm sector and openness correlate significantly—unsurprisingly, as service firms tend to be more domestically oriented.

A.9 Effect of Question Ordering on One-Year-Ahead Exchange Rate Forecasts

One may argue that the tests ran in this paper fail to provide a sensitive benchmark about the observed level of forecast inconsistencies. In order to put the inflation-related inconsistencies into perspective, we run a placebo test. In the survey, respondents are asked to provide a one-year-ahead point forecast for the exchange rate of the

Table A.11. Exchange Rate Forecasts and Question Ordering

Quarter	Obs.		Mean Forecast		Treatment Effect	
	N_D	N_P	τ_D	τ_P	$\tau_D - \tau_P$	p-value
EUR/CHF						
2014:Q4	56	60	1.206	1.207	–0.001	0.781
2015:Q1	54	59	1.071	1.065	0.006	0.493
2015:Q2	50	54	1.045	1.044	0.001	0.899
2015:Q3	52	49	1.073	1.088	–0.014	0.038
2015:Q4	56	56	1.085	1.084	0.002	0.753
2016:Q1	51	56	1.090	1.091	–0.001	0.903
2016:Q2	52	50	1.107	1.096	0.012	0.117
2016:Q3	51	50	1.096	1.094	0.002	0.655
2016:Q4	48	51	1.070	1.082	–0.011	0.118
2017:Q1	54	51	1.093	1.079	0.014	0.221
2017:Q2	48	42	1.094	1.108	–0.014	0.252
2017:Q3	49	51	1.131	1.140	–0.009	0.164
Pooled	621	629	1.098	1.099	–0.001	0.753
USD/CHF						
2014:Q4	53	59	0.984	0.985	–0.001	0.965
2014:Q1	53	58	0.992	0.984	0.008	0.437
2015:Q2	49	54	0.970	0.969	0.002	0.841
2015:Q3	52	49	0.988	0.984	0.005	0.525
2015:Q4	54	54	1.019	1.008	0.011	0.176
2016:Q1	51	53	1.002	1.006	–0.004	0.553
2016:Q2	52	49	1.004	0.993	0.010	0.251
2016:Q3	50	49	0.994	0.995	–0.001	0.900
2016:Q4	46	51	1.009	1.009	–0.000	0.990
2017:Q1	52	51	1.016	1.007	0.009	0.499
2017:Q2	47	40	0.987	0.989	–0.003	0.853
2017:Q3	47	50	0.983	0.980	0.003	0.699
Pooled	606	617	0.996	0.992	0.004	0.209

Note: The table displays, for each quarter of the experiment, the number of respondents N_i and the average exchange rate forecast τ for each group $i = P, D$ as well as the difference thereof. The last column displays the p-value of the t-test that this difference $\tau_D - \tau_P$ is different than zero (assuming equal variances). The last row considers the pooled sample.

Swiss franc vis-à-vis the euro and the U.S. dollar. For this placebo test, exchange rate forecasts are good candidates because they are specific and quantitative, and are being asked shortly before the inflation forecasts. Significant differences between the two groups P and D would cast doubt on our treatment, as they would question the direct link between observed differences in the inflation forecasts and question ordering itself.

In this respect, Table A.11 displays, for each quarter of the experiment, the number of respondents N_i and the average exchange rate forecast τ for each group $i = P, D$ as well as the difference thereof, for both currency pairs. The last column displays the p-value of the t-test that this difference $\tau_D - \tau_P$ is different than zero (assuming equal variances). The last row of each panel considers the pooled sample.

There does not seem to be a pattern in the difference in forecasts between the two groups. Out of the 24 quarterly tests run in Table A.11, we reject the null hypothesis of equal mean forecast only once at the 10 percent level (in 2015:Q3 for the EUR/CHF), which falls well within the type-I error rate. This provides additional evidence that discrepancies in inflation-related forecasts between groups are explained by question ordering rather than fortuitous, unobservable differences.

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Cash in the Pocket, Cash in the Cloud: Cash Holdings of Bitcoin Owners*

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Are private digital currencies such as Bitcoin a substitute for physical cash? We test this hypothesis using data from the Bank of Canada's Bitcoin Omnibus Survey. We estimate the effect of Bitcoin ownership on the level of cash holdings. We find a positive correlation between Bitcoin ownership and cash holdings. This effect remains after accounting for selection into ownership. On average, Bitcoin owners hold 83 percent

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(in 2018) to 95 percent (in 2017) more cash than non-owners. Quantile regressions find that Bitcoin ownership has a nonlinear effect on cash holdings. The difference varies from 63 percent (25th quantile) to 176 percent (95th quantile) in 2017. Our results provide evidence that Bitcoin adopters also hold cash.

JEL Codes: E4, C12, O51, O33.

1. Introduction

In a speech in February 2020, Bank of Canada Deputy Governor Tim Lane discussed two potential reasons for issuing central bank digital currency (CBDC): (i) if cash demand falls to a negligible level, and (ii) if private digital currencies make serious inroads. In Canada, there has been a documented decline in the use of cash by consumers for undertaking point-of-sale transactions over the last decade. The 2017 Methods-of-Payment (MOP) survey shows that the share of cash used for retail transactions declined from 54 percent in 2009 to 33 percent in 2017 (see Henry, Huynh, and Welte 2018). Even so, cash remains popular among certain demographic groups (i.e., older, less-educated, and lower-income groups) and for certain types of transactions (e.g., small-value transactions or payments at bars/restaurants). For some demographic groups, cash is also commonly used as a convenient store of value. Other advanced economies have witnessed similar patterns of cash use at the point of sale (POS). For example, Bagnall et al. (2016) undertake an international comparison across seven countries showing that cash is resilient.[1]

The country that has been touted as being closest to a cashless society is Sweden, due primarily to a lack of consumer demand for cash (see Sveriges Riksbank 2017, 2018a, 2018b). Engert, Fung, and Segendorf (2019) undertake a cross-country comparison of Canada and Sweden to understand the potential drivers of the differences between the two countries. They find that both countries have similar payment infrastructures, so the difference in cash use is due to (i) the legal tender status of banknotes, and (ii) banking

[1]The seven countries are Australia, Austria, Canada, France, Germany, Netherlands, and the United States of America.

regulations related to secure deposits in Sweden. In addition, they argue that cash demand has two components: transactional and non-transactional. In Canada and many other countries, banknotes in circulation continue to grow at pace with GDP, while at the same time cash used for payments is declining. The overall stable or increasing demand for cash is therefore thought of as primarily a store-of-value motive.

Two key considerations are relevant for assessing whether the criteria for issuing CBDC will be met in the future. First is the role of consumer preferences in driving the demand for cash and alternatives.[2] What characteristics of cash do consumers value, and would these translate to cash as manifested in a digital form? Why might consumers want a digital form of cash? Characteristics that consumers deem important for in-person transactions—such as speed, ease of use, etc.—may not be as relevant in an online setting. For example, Huynh et al. (2020) estimate the demand for payment services and find that a CBDC could potentially substitute for cash and debit card payments up to a 25 percent market share; however, this would require it to combine the best features of both cash and debit cards and be compelling enough for widespread acceptance by merchants.

Second, to assess whether private digital currencies are making inroads, it is important to understand the extent to which they function for consumers as a method of payment versus a store of value or investment (or some combination; see Glaser et al. 2014). Bitcoin was originally developed more than a decade ago with the purpose of functioning as a decentralized currency (Nakamoto 2008); that is, it would provide economic agents with the ability to make digital peer-to-peer payments without the need for a trusted third party (Böhme et al. 2015). However, the stunning increase in the price of Bitcoin, which rose from USD$1,000 in late 2016 to a peak of almost USD$20,000 in late 2017, has led many to view Bitcoin as something more akin to a "cryptoasset" than a cryptocurrency.

[2]Kennickell and Kwast (1997) presciently and accurately summarized the point almost 25 years earlier in distinguishing from a supply-side approach to studying electronic payments: "What types of products are consumers likely to be actually willing to pay for? What are the characteristics of current and likely future purchasers of electronic products and services? How quickly will consumers adopt electronic technologies?"

To better understand consumer adoption and use of the most popular private digital currency, Bitcoin, the Bank of Canada commissioned the Bitcoin Omnibus Survey (BTCOS) in 2016 (see Henry, Huynh, and Nicholls 2018). The survey has been administered annually in subsequent years (see Henry, Huynh, and Nicholls 2019 and Henry et al. 2020).[3] In the current paper we use data from the 2017 and 2018 BTCOS. The 2017 BTCOS introduced a question designed to measure Canadian consumers' cash holdings—that is, cash held in the wallet, purse, or pockets. A striking finding was that Bitcoin owners tend to hold noticeably more cash, both on average and at the median, compared with non-owners. This finding suggests that digital currencies are not currently displacing cash, even in an increasingly digital world. It also corroborates a similar finding by Fujiki and Tanaka (2014). However, it naturally raises questions about how to properly interpret this finding, specifically in terms of whether there may be factors driving *both* cash holdings and Bitcoin ownership. For example, Bitcoin owners may prefer anonymous liquidity, and hence cash may be a hedge (or vice versa); or, some Bitcoin owners may not trust institutions such as government or banks, leading to large cash holdings outside of traditional financial institutions. These sources of selection induce endogeneity that is likely to bias estimates of the effect of Bitcoin ownership on cash holdings.

Therefore, considering these potential sources of endogeneity, this paper aims to estimate the effect of Bitcoin ownership on the level of consumer cash holdings in Canada. In doing so, we also examine whether there are distributional effects present in the relationship between cash holdings and Bitcoin ownership. Anticipating possible sources of selection, both the 2017 and 2018 BTCOS were designed with a question that can be used as an exclusion restriction/instrumental variable: "What percentage of Canadians do you think will be using Bitcoin 15 years from now?" This variable works well as an exclusion restriction because owners are more optimistic about the prevalence of future Bitcoin use; however, there is no obvious direct relationship with the current level of cash holdings. To

[3]The BTCOS was among the first in terms of consumer-focused surveys dedicated to Bitcoin, similar to pioneering research by Polasik et al. (2015) and Schuh and Shy (2016).

further improve identification, we exploit differences in the functional form of age effects between the model for Bitcoin ownership and the model for cash holdings.[4]

Based on the results that control for selection, we find that the difference in cash holdings between Bitcoin owners and non-owners varies from 39 percent (in 2018) to 63 percent (in 2017) at the 25th quantile of cash, and from 176 percent (in 2017) to 203 percent (in 2018) at the 95th quantile of cash. The mean effect varies from 82 percent in 2018 to 95 percent in 2017. These results suggest that Bitcoin adopters share commonalities with cash-intensive consumers.

The paper is organized as follows: Section 2 describes the 2017 and 2018 BTCOS, Section 3 discusses the identification strategy, while Section 4 presents our findings. Section 5 concludes.

2. Data Overview

2.1 The Bitcoin Omnibus Surveys

Our analysis uses data from the 2017 and 2018 Bitcoin Omnibus Surveys (BTCOS), commissioned by the Currency Department at the Bank of Canada and conducted by market research firm Ipsos. The 2017 BTCOS is an extension to what was considered a pilot survey in 2016. This pilot, conducted in two waves in December 2016, was designed primarily to obtain basic measurements concerning public awareness and ownership of Bitcoin in Canada. As the price of Bitcoin increased rapidly over the course of 2017, the Bank of Canada decided to conduct a follow-up to the pilot with additional questions. The 2017 BTCOS was in the field December 12–15, 2017, corresponding to a (then) historical peak in the price of Bitcoin. By contrast, the 2018 survey was conducted in November and early December 2018, when the price of Bitcoin was close to a minimum following a year-long decline.

Respondents to the BTCOS are recruited via an online panel managed by Ipsos and complete the survey in an online format. The core components of the survey based on the 2016 pilot are as follows:

[4]Using non-linearities as an identification mechanism for two-stage models was suggested by Dong (2010) and Escanciano, Jacho-Chávez, and Lewbel (2016).

awareness of Bitcoin; ownership/non-ownership of Bitcoin; amount of Bitcoin holdings; and reasons for ownership/non-ownership. The 2017 and 2018 surveys contain additional content aimed at providing a deeper understanding of the motivation of Bitcoin owners and their usage behavior, including beliefs about the future adoption and survival of Bitcoin; knowledge of Bitcoin features; price expectations; use of Bitcoin for payments or person-to-person transfers; preferred methods of payment for online purchases; and ownership of other cryptocurrencies. Most importantly for the purposes of this paper, the 2017 and 2018 BTCOS ask respondents to report the amount of *cash on hand*, that is, the cash currently held in their wallet, purse, or pockets. We refer to this throughout the paper as a respondent's *cash holdings*.

In 2017, a total of 2,623 Canadians completed the BTCOS, of which 117 self-identified as Bitcoin owners. In 2018, the BTCOS was answered by 1,987 Canadians, of which 99 reported they own Bitcoin. In addition to content questions, respondents are also asked to provide demographic information. Sampling for the survey is conducted to meet quota targets for the Canadian population relative to age, gender, and region. Once the sample is collected, the Bank of Canada conducts an in-depth calibration procedure to ensure that the sample is representative of the adult Canadian population across a variety of dimensions (see Henry et al. 2019 for details).

2.2 Descriptive Statistics

Table 1 presents the main finding that motivates our subsequent empirical analysis—namely, that Bitcoin adopters hold noticeably more cash than non-adopters.[5,6] Specifically, Bitcoin adopters in the

[5]For the purposes of this table only, we consider an "adopter" to be anyone who currently owns *or* previously owned Bitcoin. This allows for an increased sample size for the calculation, as the BTCOS has a question that allows us to identify past owners. Further, in the Methods-of-Payment (MOP) survey, a Bitcoin adopter is identified as anyone who used Bitcoin within the past year; since we don't know whether or not the respondent still owns Bitcoin, this definition of "adopter" for the BTCOS is more comparable with the MOP.

[6]In a paper about Bitcoin ownership in Canada, Balutel et al., "Explaining Bitcoin Ownership," (2024) show that Bitcoin adopters continue to hold significantly more cash than non-adopters all the way to 2021, while also assessing the possible reasons why this is the case.

Table 1. Cash and Bitcoin Adoption in Canada

	Cash on Hand		No Cash	
	Mean	**Median**	**Percentage**	**N**
Bitcoin Adopters				
2018 BTCOS	518	120	6%	144
2017 BTCOS	434	100	5%	154
2017 MOP	320	65	8%	93
Non-adopters				
2018 BTCOS	171	40	8%	1,843
2017 BTCOS	104	40	8%	2,469
2017 MOP	108	40	9%	3,127
2013 MOP	84	40	6%	3,663

Note: Data are from the Bitcoin Omnibus Survey and Methods-of-Payment Survey. BTC adopters are both current and past owners (BTCOS), and those who have used digital currency at least once in the past year (MOP). "No cash" is the percentage of respondents not having any cash on their person.

BTCOS hold at least three times more cash, on average, than non-adopters, and anywhere from \$60 to \$80 more cash at the median. As a point of comparison, we also consider data from the Bank of Canada's Methods-of-Payment (MOP) survey, a more general and comprehensive consumer payments survey conducted in 2013 and 2017 (see Henry, Huynh, and Shen 2015 and Henry, Huynh, and Welte 2018). The MOP has the exact same cash holdings question and also includes a question in 2017 to identify Bitcoin adopters. The MOP results are in line with the findings from the 2017 and 2018 BTCOS: adopters hold just under three times more cash than non-adopters, and \$25 more cash at the median. We further note that on the extensive margin, non-adopters in the BTCOS are more likely to hold zero dollars in cash (8 percent) compared with adopters (6 percent in 2018; 5 percent in 2017); however, this finding is not as strong in the MOP data.

Table 2 provides a demographic breakdown of Bitcoin owners[7] versus non-owners, along with their average cash holdings. In both 2017 and 2018, Bitcoin owners tend to be younger in age, employed,

[7]From this point on we consider Bitcoin owners to mean *current* owners.

Table 2. Demographics of Bitcoin Owners and Non-owners in Canada and Their Cash Holdings

	2017				2018			
	Non-owners		Owners		Non-owners		Owners	
Demographic	(1) Proportion	(2) Mean Cash	(3) Proportion	(4) Mean Cash	(5) Proportion	(6) Mean Cash	(7) Proportion	(8) Mean Cash
Male	0.47	99	0.75	599	0.48	160	0.63	565
Female	0.53	68	0.25	590	0.52	78	0.37	884
18–34	0.25	72	0.71	711	0.26	130	0.55	849
35–54	0.34	78	0.25	445	0.34	103	0.32	716
55+	0.40	92	0.04	137	0.40	109	0.13	120
High School	0.43	74	0.36	415	0.44	119	0.19	694
College	0.31	73	0.22	248	0.30	101	0.33	461
University	0.27	93	0.42	835	0.26	116	0.48	840
<30k	0.30	68	0.34	370	0.31	116	0.16	458
30k–69k	0.44	85	0.38	718	0.41	101	0.46	748
70k+	0.27	107	0.27	904	0.28	148	0.38	798
Employed	0.60	86	0.86	603	0.60	128	0.83	715
Not Employed	0.40	75	0.14	560	0.40	88	0.17	647
British Columbia	0.13	71	0.16	369	0.13	87	0.17	1,039
Prairies	0.18	83	0.17	1,002	0.18	114	0.21	1,130
Ontario	0.39	79	0.34	735	0.38	116	0.38	605
Quebec	0.23	91	0.28	298	0.24	115	0.21	376
Atlantic	0.07	78	0.05	741	0.07	114	0.04	342
Btc Literacy: Low	0.57	79	0.24	356	0.63	116	0.19	631
Btc Literacy: Medium	0.38	94	0.49	699	0.32	115	0.52	624
Btc Literacy: High	0.05	99	0.27	623	0.05	64	0.29	861
FL Literacy: Low					0.26	143	0.38	1,123
FL Literacy: Medium					0.36	84	0.33	570
FL Literacy: High					0.37	115	0.29	330
N	2,506		117		1,987		99	

Note: The table presents the proportion of Bitcoin owners and non-owners by demographic characteristics and the mean of cash holdings of Bitcoin owners and non-owners by demographic characteristics. The first four columns (1–4) are the results for the year 2017 and the last four columns (5–8) are for the year 2018. For each year the first two columns are the proportion of Bitcoin non-owners (1, 5) and the cash holdings for Bitcoin non-owners (2, 6), while the last two columns are the proportions of Bitcoin owners (3, 7) and the cash holdings of Bitcoin owners (4, 8).

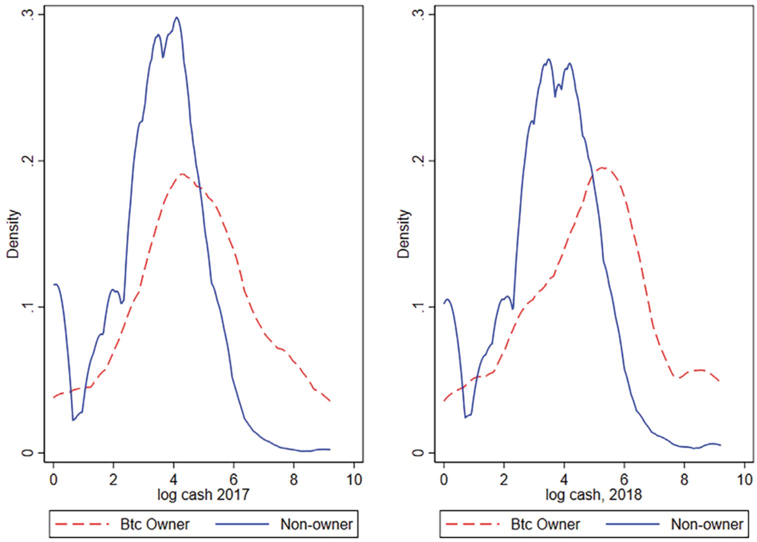
and male. For example, the 18- to 34-year-old age group accounts for 71 percent of Bitcoin owners in 2017 and 55 percent in 2018. By contrast, among non-owners this demographic group represents only about a quarter of the sample. Similarly, males are noticeably over-represented among Bitcoin owners (75 percent in 2017; 63 percent in 2018) when compared with non-owners (47 and 48 percent in 2017 and 2018, respectively). As one might expect, more Bitcoin owners are categorized as “high” in Bitcoin knowledge. Only 5 percent of non-owners achieve a perfect score on the three questions designed to test Bitcoin knowledge, whereas more than a quarter of Bitcoin owners achieve this score in both years. Finally, looking at changes from 2017 to 2018, there are notable differences in the composition of Bitcoin owners with respect to their level of income and education. In 2017 there is little difference between Bitcoin owners and non-owners in terms of their income profile, while in 2018 Bitcoin owners are relatively more likely to have a household income over $70,000. Similarly, there is a shift in the profile of Bitcoin owners from low education (high school) to higher levels of education (college and university) between 2017 and 2018.

Looking at cash holdings, we find that demographic groups associated with Bitcoin ownership also tend to have higher cash holdings. For example, in both 2017 and 2018, Bitcoin owners aged 18 to 34 years hold more than five times more cash on hand, on average, than owners aged 55 and older. This contrasts with patterns among non-owners, where older respondents tend to hold similar (in 2018) or more (in 2017) cash than younger age groups. Similarly, Bitcoin owners with the highest levels of income and education (over $70,000 and university educated, respectively) hold noticeably more cash than their lower-income and lower-education counterparts. One particularly stark association from 2018 involves financial literacy.[8] Bitcoin owners are more likely to have low financial literacy relative to non-owners and are also one of the most cash-intensive groups,[9] holding $1,123 on average.

[8] The 2018 BTCOS includes three standardized questions that measure respondents’ financial literacy; see Lusardi and Mitchell (2014).

[9] More findings about differences in financial literacy between Bitcoin owners and non-owners can be found in Balutel et al., “Crypto and Financial Literacy,” (2024).

Figure 1. Density of Cash Holdings (in logs) for Bitcoin Owners and Non-owners



Note: The panels plot the density of cash holdings (in logs) for Bitcoin owners (red line) and non-owners (blue line) for 2017 (left) and 2018 (right). Data are from the 2017 and 2018 BTCOS.

Finally, Figure 1 shows the distribution of log-transformed cash holdings by Bitcoin owners and non-owners. We see that in both 2017 and 2018, Bitcoin owners hold more cash across almost the entire support, except for lower levels of cash (roughly, below the 15th quantile) where the distributions are similar for the two groups. The figure also demonstrates that not only do Bitcoin owners hold higher levels of cash at the mean, the distribution is also skewed heavily to the right. Further, the distribution of non-owners is heterogeneous with multiple modes. These two observations suggest that any estimation approach based on mean average responses of cash holdings by Bitcoin holders will be affected by this observed skewness and heterogeneity. Consequently, while we look at the mean responses of cash holdings as a benchmark model, we also analyze the quantiles of cash.

3. Identification Strategy

Identifying the relationship that links cash holdings to Bitcoin ownership builds on information available from the BTCOS, certain characteristics of the data, and the interactions present in the data. Naively, we can use the question about Bitcoin ownership to separate owners from non-owners and, as a benchmark, estimate an ordinary least squares (OLS) linear regression model where the explanatory variable of interest is Bitcoin ownership. However, our demographic analysis suggests that ownership of Bitcoin is *not* exogenous. To confirm this fact, Table 3 shows the statistical differences in means for certain demographic characteristics, namely age, gender, employment, education, number of children, marital status, and grocery shopping. The grocery shopping variable indicates whether the respondent is responsible for doing all or part of the household's grocery shopping, a proxy for the level of domestic responsibility.

These differences suggest that the unconditional mean effects of Bitcoin ownership on cash holdings should not be identical to the conditional mean effects. In particular, for 2017, Bitcoin owners are younger (almost 13 years mean age difference), 60 percent more likely to be male,[10] and more likely to be employed and have higher education (43 percent more likely to be employed and 55 percent more likely to have completed some university-level education). Bitcoin owners are also less likely to be responsible for the household's grocery shopping. In 2018, while there are still observed differences between Bitcoin owners and non-owners, some of these differences are reduced—there is only an 11-year difference in age and owners are only 31 percent more likely to be male. At the same time, in 2018 there are increased differences between Bitcoin owners and non-owners relative to education (84 percent more likely to be university educated) and income categories. The differences in the distribution of observable characteristics suggest that owning Bitcoin is selective, and therefore we should account for the selection in our identification strategy. The difference in findings between 2017

[10]To compute the percentage change between male owners and male non-owners we use the following: (proportion of owners (75) – proportion of non-owners (47))/proportion of non-owners (47).

Table 3. Mean Differences for Demographic Characteristics between Bitcoin Owners and Non-owners

	2017		2018	
	(1) $X_{NoBtc} - X_{Btc}$	(2) t-test	(3) $X_{NoBtc} - X_{Btc}$	(4) t-test
Age	13.40***	12.39	11.11***	7.55
Gender: Female	0.276***	6.48	0.153***	2.99
Income: <30k	–0.035	–0.76	0.164***	4.05
Income: 30k–69k	–0.029	–0.64	–0.148***	–2.86
Income: >70k	0.000	–0.001	–0.129***	–2.70
British Columbia	–0.064	–1.68	–0.026	–0.70
Prairies	0.035	1.01	–0.023	–0.59
Ontario	0.007	0.15	–0.020	–0.39
Quebec	–0.004	–0.11	0.053*	1.30
Atlantic	0.027	1.19	0.016	0.71
Employed	–0.262***	–7.50	–0.229***	–5.53
Education: High School	0.057*	1.59	0.157***	5.37
Education: College/CEGEP/Trade School	0.076**	1.79	0.030	–0.614
Education: University	–0.133***	–2.83	–0.187***	–3.67
Number of Kids: No Kids	0.166***	3.60	0.261***	5.12
Marital Status: Not Married/CL	–0.047	–1.01	0.052	1.04
Grocery Shopping: Not All of It	–0.110***	–2.43	–0.092**	–1.83

Note: Columns 1 and 3 present the difference in means between Bitcoin non-owners and owners for years 2017 and 2018, while columns 2 and 4 present the t-test for the difference in means for the two years. ***, **, and * represent 1 percent, 5 percent, and 10 percent significance, respectively. Data are from the Bitcoin Omnibus Survey 2017 and 2018.

and 2018 may imply that the selection effect is stronger in 2017 than 2018.

We have seen from summary statistics that Bitcoin adopters hold more cash compared to non-adopters. This raises the possibility of some simultaneity that links cash holdings and Bitcoin ownership—that is, unobservable factors that drive people to both adopt Bitcoin and also hold high levels of cash. For example, Bitcoin owners may prefer anonymous liquidity, and hence cash may be a hedge (or vice versa). Some Bitcoin owners may not trust institutions such as government or banks, leading to large cash holdings outside of traditional financial institutions. Alternatively, Bitcoin owners that would like to use it as a payment method may be forced to rely on cash while the acceptance of Bitcoin by merchants remains low. To solve these selection issues, we propose using identification methods that account for endogenous selection via a control function (CF) approach.[11] The CF approach is further used to quantify the effect of Bitcoin ownership on quantiles of cash.

In what follows, we describe our two main hypotheses of interest regarding the link between Bitcoin ownership and cash holdings; for each hypothesis, we consider a version that does not account for selection, as well as one that does account for selection. Then, we outline the models used for testing each hypothesis.

3.1 Expected Cash Holdings

The first question of interest relates to average (or mean) cash holdings, and tests the following hypothesis:

$$H_{01} : E(Cash|Btc, X, P) > E(Cash|No - Btc, X, P), \qquad (1)$$

where X includes individual characteristics of gender, age, education, marital status, number of children, employment status, household grocery-shopping participation, and income, and P is province fixed effects. In other words, this hypothesis tests if the average holdings of cash are higher for Bitcoin owners than for non-owners.

As a benchmark, we estimate a simple linear OLS model of the form

$$cash_{i,t} = \alpha + \beta Btc_{i,t} + \gamma X_{i,t} + \delta P_j + u_{i,t}, \qquad (2)$$

where $cash_{i,t}$ is the log of cash holdings of individual i at time $t \in \{2017, 2018\}$;[12] $Btc_{i,t}$ is equal to 1 if the respondent i from period t is a Bitcoin owner and zero otherwise; $X_{i,t}$ is a set of respondent characteristics for individual i from period t; P_j is regional fixed effects; and $u_{i,t}$ is the cross-section specific error term.

The parameter of interest is β, or the effect of Bitcoin ownership on cash holdings. If Btc happens to be randomly assigned, then the β parameter can be treated as a causal parameter. However, we

[11] Wooldridge (2015) provides an excellent overview.

[12] As there are two cross-sections, at each period t there is a unique individual i that is not the same across the two cross-sections.

know that there is selection into ownership of Bitcoin and this selection will generate bias. Heckman and Robb (1985) provide a method to model the selection by using a two-stage estimation procedure. In the first stage, the endogenous variable (Btc) is projected onto an exclusion restriction and a set of observed characteristics via a binary choice model:

$$Btc_{i,t} = Pr(Z_{i,t}, X_{i,t}, P_j) + \epsilon_{i,t}, \tag{3}$$

where $Z_{i,t}$ is the exclusion restriction of individual i from period t, and $\epsilon_{i,t}$ is the error term that has an independent and identically distributed (i.i.d.) logistic distribution.

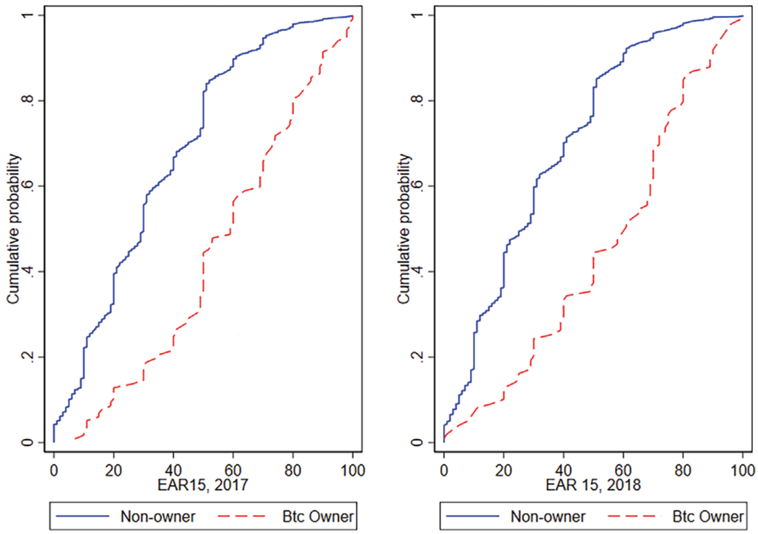
The exclusion restriction we utilize is based on the survey question about expectations of the future adoption rate of Bitcoin, namely: "What percentage of Canadians do you predict will be using Bitcoin 15 years from now?" We call this variable $EAR15$. It is positively correlated with Bitcoin ownership, as owners tend to have a more optimistic outlook on the future adoption of Bitcoin.[13] However, $EAR15$ does not directly influence a respondent's current level of cash holdings—the survey question specifically asks respondents to count the amount of cash in their wallet, purse, or person during the survey, and they cannot re-optimize their cash holdings. Therefore, $EAR15$ should not be correlated with cash holdings and indeed the correlation coefficient between $EAR15$ and cash holdings is 0.06.

Additionally, Figure 2 illustrates the cumulative distribution function (CDF) plot of $EAR15$ for Bitcoin owners versus non-owners in both 2017 and 2018. The CDFs of the two distributions do not intersect. In more technical terms, $EAR15$ of Bitcoin owners first-order stochastic dominates (FOSD) the distribution of $EAR15$ for non-owners.[14] The medians of the distributions show that non-owners believe the expected adoption rate will be around 30 percent, while owners believe it will be around 60 percent. The $EAR15$ variable also satisfies the conditional independence assumption as in Abadie, Angrist, and Imbens (2002). Consequently, $EAR15$ acts as a valid exclusion restriction to delineate between Bitcoin owners and non-owners.

[13]The correlation coefficient between $EAR15$ and Bitcoin ownership is 0.24.

[14]We conducted an FOSD test based on Kolmogorov-Smirnov that resulted in a p-value equal to 1.

Figure 2. Cumulative Distribution Function of the Expected Adoption Rate by Bitcoin Owners and Non-owners

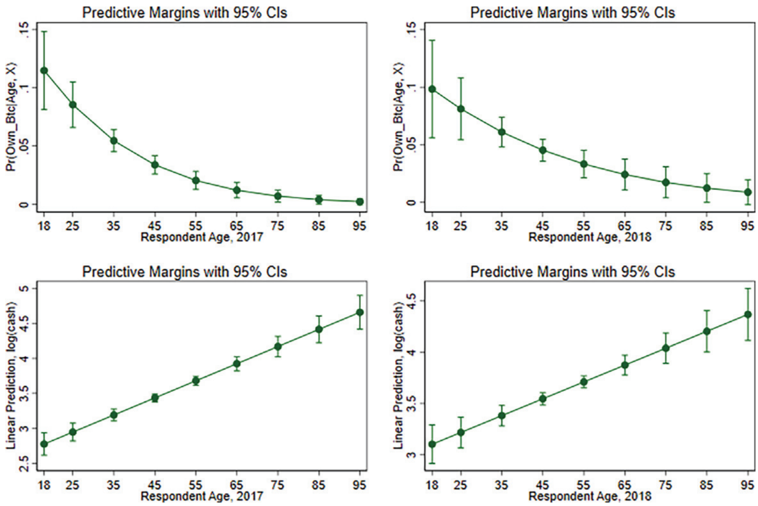


Note: The panels plot the cumulative distribution functions (CDFs) of expected adoption rate of Bitcoin ($EAR15$) for Bitcoin owners (red line) and non-owners (blue line) for 2017 (left) and 2018 (right). The two distributions are statistically different. Data are from the 2017 and 2018 BTCOS.

To further improve identification, we exploit differences in age effects between the model for Bitcoin ownership (Equation (3)) and the model for cash holdings (Equation (2)). Figure 3 shows the predicted probabilities of Bitcoin ownership in 2017 and 2018 (top panels), as well as predicted cash holdings (bottom panels), as a function of age. The figure clearly shows that age has a non-linear effect on ownership, while it has a linear effect on cash holdings. This non-linearity in the first stage can be exploited in identification as suggested by Dong (2010) and Escanciano, Jacho-Chávez, and Lewbel (2016).

To exploit the non-linear effect of age on Bitcoin ownership, we introduce fractional polynomial (FP) terms of age. The use of FP as a method to obtain a more robust non-linear representation of the relationship between the explanatory variable of interest and a

Figure 3. Predictive Margins of Bitcoin Ownership and Cash Holdings as Functions of Age



Note: The top panels plot the predicted margins of the probability of Bitcoin adoption as a function of age (first-stage equation) for 2017 (top left) and 2018 (top right). The bottom panels plot the predicted margins of the cash holdings (log cash) as a function of age (second-stage equation) for 2017 (bottom left) and 2018 (bottom right). Data are from the 2017 and 2018 BTCOS.

binary choice outcome was previously studied by Williams (2011). This study suggests that use of FP is a better alternative to other methods designed to capture non-linearity in discrete choice settings. Consequently, we augment our first-stage model with FP terms as follows:

$$Btc_{i,t} = Pr(Z_{i,t}, X_{i,t}, Age^{p_k}_{i,t}, P_j) + \epsilon_i, \tag{4}$$

where $Age^{p_k}_{i,t}$ represents the FP terms of age for individual i in period t. In our specification, the selected FP is of order two and is provided by Royston and Altman (1994)'s algorithm, which provides the best fit between the predictor (here, age) and the outcome (here, Bitcoin ownership).

Finally, to account for the endogenous selection into Bitcoin ownership as well as possible sources of simultaneity, we estimate a second-stage model that augments Equation (2) with a CF. The estimated residuals from the first stage with FP age terms (Equation (4)) are used as a correction term in this second stage; as the endogenous variable is binary, we have to construct appropriate residuals that are not correlated with the error term in the main equation, and also have statistical properties similar to those used in a least-squares approach. As we chose the logit link function to estimate the probability of Bitcoin ownership, we chose as a CF the deviance residuals ($\widehat{\epsilon_{i,t}}$) since their distribution is closer to the distribution of residuals from OLS regression models:

$$\widehat{\epsilon_{i,t}} = sign_{i,t}\sqrt{\begin{array}{l}-2(Btc_{i,t}\log(Pr(Z_{i,t},\widehat{X_{i,t},A}ge^{p_k}_{i,t},P_j)) \\ \quad +(1-Btc_{i,t})\log(1-Pr(Z_{i,t},\widehat{X_{i,t},A}ge^{p_k}_{i,t},P_j)),\end{array}} \tag{5}$$

where $sign_{i,t}$ is positive if $Btc_{i,t}$ takes the value of 1 and negative if $Btc_{i,t}$ takes the value of 0.

The first testable hypothesis is therefore modified as follows:

$$\begin{aligned} H^{'}_{01} &: E(Cash|Btc, EAR15, X, P) \\ &> E(Cash|No-Btc, EAR15, X, P), \end{aligned} \tag{6}$$

where $EAR15$ is the exclusion restriction. This hypothesis is tested by estimating the following second-stage model, where the CF term is introduced as a correction:

$$cash_{i,t} = \alpha + \beta Btc_{i,t} + \gamma X_{i,t} + \delta P_j + \phi\widehat{\epsilon_{i,t}} + u_{i,t}. \tag{7}$$

3.2 Quantiles of Cash Holdings

Recall that Figure 1 shows that the distribution of cash holdings has a heavy right tail for Bitcoin owners and is multimodal for non-owners. The average cash holding amount is affected by these characteristics of the data, and therefore an additional hypothesis of interest tests if Bitcoin owners hold more cash than non-owners across all quantiles of cash:

$$H_{02} : Q_\tau(Cash|Btc, X, P) > Q_\tau(Cash|No-Btc, X, P), \tag{8}$$

where Q_τ is the τ-th quantile and X and P are defined previously. This hypothesis can be tested using the following reduced-form specification:

$$Q_{Cash}(\tau)_{i,t} = \alpha^\tau + \beta^\tau Btc_{i,t} + \gamma^\tau X_{i,t} + \delta^\tau P_j + u^\tau_{i,t}. \tag{9}$$

This model can be viewed as a conditional quantile treatment-effects-type model. The underlying assumption required for identification of quantile treatment effects is that the errors are orthogonal to the treatment (here, Bitcoin ownership indicator) and that selection is exogenous. As previously argued, we do not believe that selection is exogenous, and to account for this we use a CF-quantile approach:

$$H^{'}_{02} : Q_\tau(Cash|Btc, EAR15, X) > Q_\tau(Cash|No - Btc, EAR15, X), \tag{10}$$

where Bitcoin owners are entering in the quantile equation via a CF, as suggested in the linear specification above. This hypothesis is estimated via the following model:

$$Q_{Cash}(\tau)_{i,t} = \alpha^\tau + \beta^\tau Btc_{i,t} + \gamma^\tau X_{i,t} + \delta^\tau P_j + \phi^\tau \widehat{\epsilon_{i,t}} + u^\tau_{i,t}, \tag{11}$$

where $\widehat{\epsilon_i}$ is the deviance residual specified in Equation (5).

4. Empirical Results

For the first hypothesis of interest, H_{01}, we estimate an OLS model of log cash holdings on Bitcoin ownership, demographic characteristics, and regional fixed effects. However, as discussed in Section 3, to properly account for endogenous selection, we need to augment this model with a correction term that requires first estimating the probability of Bitcoin ownership, in order to test H'_{01}. Consequently, we start by presenting results from the *extensive margin* analysis, which quantifies the effects of observable characteristics on the probability of owning Bitcoin (also referred to as the propensity score). We further augment the propensity score model with the exclusion restriction ($EAR15$) and non-linear age terms, to estimate the probability of owning Bitcoin that is ultimately used for the first stage of the two-stage CF approach. Following this, we present results related to both the first and second hypotheses of interest (mean effects and quantile effects, respectively), both with and without the correction for selection.

4.1 Probability of Owning Bitcoin

The results of the extensive margin analysis are presented in Table 4; the first four columns are results for the year 2017, while the last four columns are for 2018. The first column models the probability of Bitcoin ownership, accounting for demographic characteristics and regional fixed effects; the second column augments the model with the $EAR15$ variable; the third column adds a quadratic age term; finally, the fourth column adds FP of age (see Section 3). The fifth to eighth columns are the equivalent models for the 2018 data.[15]

A concern associated with this estimation is that Bitcoin ownership can be considered a "rare event," as only around 5 percent of Canadians are Bitcoin owners. To address this potential issue, the probability models are adjusted to account for rare events via a penalized likelihood approach, initially introduced by Firth (1993) for generalized linear models and extended for logistic regression models by Heinze and Schemper (2002). The correction for rare events does not provide any additional information, being similar to the classical logistic model, and therefore we report only the logistic results.[16]

The results from 2017 emphasize the role of gender, age, employment status, and number of children on Bitcoin ownership. In particular, being older, female, and having children have a significant and negative impact on the likelihood of owning Bitcoin, while

[15] Given that only 5 percent of the sample represents owners of Bitcoin (117 observations in 2017 and 99 in 2018), we check if each cell associated with the variables used in the analyses has sufficient observations to do a proper analysis. VanVoorhis and Morgan (2007) point out that for a chi-squared test, five observations per cell are minimal, while seven observations per cell are the minimum needed for a mean comparison. For almost all the cells we have much more than the minimum as suggested by these guidelines. One cell with problems is the retired cell, therefore we combine retired with unemployed and not in labor force to obtain a relevant comparison cell with employed. We provide empirical estimates to demonstrate that these minimum cells do not affect the estimation results.

[16] The penalized likelihood results are available in Table A.1 in the appendix.

Table 4. Probability of Bitcoin Ownership

Variables	(1) 2017	(2) 2017	(3) 2017	(4) 2017	(5) 2018	(6) 2018	(7) 2018	(8) 2018
Respondent Age	–0.0680***	–0.0563***	–0.0646		–0.0558***	–0.0363***	–0.139***	
	(0.00926)	(0.00944)	(0.0561)		(0.0108)	(0.0116)	(0.0388)	
Age^2			0.000103				0.00117***	
			(0.000691)				(0.000423)	
Age^{P1}				–19.31***				–0.058***
				(6.373)				(0.012)
Age^{P2}				49.23***				0.027***
				(11.07)				(0.006)
Gender: Female	–1.300***	–1.357***	–1.357***	–1.355***	–0.928***	–0.802***	–0.787***	–0.796***
	(0.210)	(0.222)	(0.222)	(0.225)	(0.223)	(0.238)	(0.243)	(0.242)
Income: 50k–99k	–0.138	–0.110	–0.109	–0.111	0.956***	1.018***	1.053***	1.070***
	(0.253)	(0.265)	(0.264)	(0.264)	(0.304)	(0.311)	(0.303)	(0.313)
Income: 100k+	–0.377	–0.353	–0.350	–0.300	0.976***	0.908**	1.000***	1.020***
	(0.294)	(0.311)	(0.309)	(0.316)	(0.365)	(0.374)	(0.366)	(0.372)
Prairies	–0.678**	–0.818**	–0.815**	–0.859**	–0.0698	–0.0359	–0.00114	0.017
	(0.339)	(0.361)	(0.360)	(0.358)	(0.370)	(0.382)	(0.385)	(0.393)
Ontario	–0.353	–0.558*	–0.557*	–0.563*	–0.210	–0.292	–0.265	–0.213
	(0.278)	(0.298)	(0.299)	(0.298)	(0.320)	(0.335)	(0.336)	(0.344)
Quebec	–0.279	–0.610**	–0.608*	–0.637**	–0.395	–0.459	–0.355	–0.327
	(0.293)	(0.311)	(0.311)	(0.311)	(0.363)	(0.384)	(0.388)	(0.395)
Atlantic	–0.759*	–0.931**	–0.928**	–0.929**	–0.387	–0.501	–0.419	–0.387
	(0.447)	(0.458)	(0.457)	(0.463)	(0.570)	(0.609)	(0.614)	(0.614)
Employment	0.783***	0.623**	0.635**	0.526*	0.121	0.173	0.353	0.251
	(0.303)	(0.307)	(0.320)	(0.318)	(0.279)	(0.286)	(0.300)	(0.306)
College/CEGEP/Trade School	–0.0980	0.0834	0.0878	0.0289	0.864**	0.911**	1.015**	0.931**
	(0.317)	(0.321)	(0.326)	(0.323)	(0.412)	(0.423)	(0.423)	(0.422)
University	0.264	0.494	0.498	0.373	0.986**	0.971**	1.054**	0.954**
	(0.288)	(0.302)	(0.306)	(0.311)	(0.396)	(0.414)	(0.416)	(0.414)
Number of Kids: No Kids	–0.468**	–0.296	–0.303	–0.352	–0.713***	–0.608**	–0.700**	–0.593**
	(0.228)	(0.234)	(0.238)	(0.237)	(0.249)	(0.271)	(0.272)	(0.275)
Marital Status: Not Married/CL	–0.299	–0.196	–0.200	–0.0801	–0.201	0.002	–0.0259	–0.018
	(0.249)	(0.257)	(0.261)	(0.269)	(0.289)	(0.291)	(0.294)	(0.294)

(*continued*)

Table 4. (Continued)

Variables	**(1) 2017**	**(2) 2017**	**(3) 2017**	**(4) 2017**	**(5) 2018**	**(6) 2018**	**(7) 2018**	**(8) 2018**
Grocery Shopping: Not All of It	–0.657***	–0.275	–0.280	–0.209	–0.529**	–0.242	–0.301	–0.244
	(0.221)	(0.229)	(0.235)	(0.236)	(0.235)	(0.241)	(0.245)	(0.242)
EAR15		0.0405***	0.0405***	0.0404***		0.0378***	0.0373***	0.0368***
		(0.00433)	(0.00434)	(0.00433)		(0.00538)	(0.00538)	(0.0054)
Constant	0.756	–1.671**	–1.526	–6.912***	–0.593	–3.348***	–1.534	–3.712***
	(0.558)	(0.658)	(1.161)	(3.522)	(0.697)	(0.943)	(1.186)	(0.843)
Observations	2,623	2,623	2,623	2,623	1,987	1,987	1,987	1,987
LR χ^2	110.4	171.3	172.9	183.4	92.43	167.5	182.4	178.2
Adj. R^2	0.175	0.270	0.270	0.276	0.162	0.246	0.254	0.260
Logit Specification Tests								
Prediction	1.56***	1.19***	1.18***	1.17***	1.65***	1.098***	1.05***	1.056***
Prediction Squared	0.098**	0.39	0.038	0.035	0.12**	0.021	0.04	0.01
LROC	0.81	0.866	0.866	0.869	0.79	0.85	0.854	0.86

Note: The first column is the benchmark probability model of Bitcoin ownership for year 2017, the second column is the benchmark augmented with EAR15, the third column adds age squared, the fourth column is the benchmark with EAR15 and augmented with two fractional polynomial terms; columns 5, 6, 7, and 8 are the symmetrical models for the year 2018. Baseline categories are male, <50k income, British Columbia region, unemployment, high school education, having children, married, and conducting all the household grocery shopping. Two additional specification tests were provided at the bottom of the table: (i) a linktest that regresses Bitcoin ownership on its prediction and squared prediction, where a significant square prediction may emphasize missing information in the Bitcoin ownership model; (ii) a test that quantifies the power of discrimination between Bitcoin owners and non-owners, where the LROC is the value of the area under receiver operating characteristic (ROC) curve. A value close to 1 suggests a high power of discrimination between Bitcoin owners and non-owners. ***, **, and * represent 1 percent, 5 percent, and 10 percent significance, respectively.

being employed has a significant and positive effect.[17] With respect to region, only the Prairies and Atlantic provinces have a significantly different (negative) effect when compared with the benchmark, British Columbia. Compared with the 2018 results (columns 5 to 8), we see a change in the demographics of Bitcoin owners, as income and education become statistically significant for Bitcoin ownership—higher education and income levels are associated with increased likelihood of owning Bitcoin.

When we augment the model with the $EAR15$ variable, we observe the predictability power of this exclusion restriction as measured by adjusted R^2 (54 percent higher adjusted R^2 in 2017 due to $EAR15$; 52 percent higher in 2018).[18] In addition to the $EAR15$ variable, recall that to improve identification in the second stage we add regressors that capture the non-linearity of age in relationship with Bitcoin ownership. Consequently, in column 3 (for 2017) and column 7 (for 2018), age squared is included as an additional explanatory variable. We see that this addition does not provide any improvement for 2017 relative to increased predictive power as measured by the adjusted R^2, and only a marginal improvement for 2018. However, when the FP of order two are added to the model along with $EAR15$ (column 4 for 2017 and column 8 for 2018), we see an increase in predictability of Bitcoin ownership for both years. Consequently, we retain this last specification as the one needed to generate the control function for the second-stage regression model.

Finally, we check the predictability power of the model specifications using logit specification tests. Results are presented at the

[17]Some of these findings are consistent with respect to other literature on the adoption and use of digital technologies more generally. For example, an OECD report from 2018 documents a persistent gap between men and women in terms of the "access, use and ownership of digital technologies" in many G20 countries (OECD 2018). Rogers (2010) documents that early adopters of new technologies are typically young, live in urban areas, and are educated and socially active.

[18]The model that augments with $EAR15$ initially has a smaller sample size (by about 15 percent) because, in both years, some of the respondents did not answer this question. We therefore check if the reduced sample suffers from additional selection issues by seeing if the average observables are significantly different in the two samples. Ultimately, this leads to modeling the missing data with a missing-at-random (MAR) imputation model where we conclude that the item non-response does not have a significant effect on outcomes. As a result of this imputation, Table 4 utilizes a new $EAR15$ variable that corrects for the missing data and the entire sample is used in the estimation.

Table 5. Probability of Bitcoin Ownership as a Function of the Exclusion Restriction Only

Logit Model with EAR15 Only	2017	2018
Variables	**Estimates 2017**	**Estimates 2018**
EAR15	0.0454***	0.0456***
	(0.0042)	(0.0048)
Constant	–5.079***	–4.878
	(0.255)	(0.282)
Linktest	2017	2018
Prediction	1.248***	1.589***
Prediction Squared	0.046	0.114
LROC	0.78	0.77
Observations	2,623	1,987

Note: Similar specification tests as at the bottom of Table 4. ***, **, and * represent 1 percent, 5 percent, and 10 percent significance, respectively.

bottom of Table 4. The model with $EAR15$ dominates the model without it by showing that there are no remaining unobservables that can improve the predictability of Bitcoin ownership. More specifically, the prediction is significant while its square is not. In terms of discrimination between owners and non-owners, the area under receiver operating characteristic (ROC) curve is 0.86 versus 0.81 without $EAR15$ (see Metz 1978). For both years, when the model with $EAR15$ is augmented with non-linear FP terms of age, there is a marginal increase in the predictability of Bitcoin ownership, while there is no increase if only the square of age is added.

An analysis using only $EAR15$ as an explanatory variable for Bitcoin ownership shows the importance of this variable for predicting the probability of owning Bitcoin, as shown in Table 5. The variable itself gives an area under the ROC of 0.78 for 2017 and 0.77 for 2018. This underlines the importance of this variable for discriminating between Bitcoin owners and non-owners.

4.2 Mean Effects of Cash Holdings

Next, we focus on the *intensive margin* of our analysis, which is designed to answer the question of interest regarding the effect of Bitcoin ownership on the usage of cash. To test the first hypothesis of interest, H_{01}, we estimate a benchmark linear specification that treats the ownership of Bitcoin as exogenous. Then, we extend the linear analysis, assuming that ownership is in fact selective using a CF approach and use this model to test H'_{01}.[19] The results of these analyses are presented in Table 6.

Column 1 of Table 6 presents the results of the benchmark model for the year 2017. The parameter estimate of Bitcoin ownership is statistically significant and equal to 1.36. This can be interpreted as, on average, Bitcoin owners hold 136 percent more cash than non-owners after controlling for age, gender, income, education, marital status, number of children, and region. Column 2 of Table 6 presents the conditional mean of cash holdings model that accounts for selection via a CF approach. The results show that the proposed correction estimates an average difference of log-cash holdings between Bitcoin owners and non-owners of 0.948. This result implies that the average cash holdings are about 95 percent higher for Bitcoin owners after controlling for selection. The demographic characteristics that are relevant for cash holdings are age (positive effect), gender-female (negative effect), and medium and higher income categories that show positive effects over the benchmark category (less than $50,000 household income). The Prairies, Ontario, and Quebec regions show positive effects over the benchmark region (British Columbia). The last two columns are the symmetric results for the year 2018. In general, the results are consistent across the two years, however the mean effects of cash holdings are lower in 2018 than in 2017 (1.18 in 2018 versus 1.36 in 2017 for the model without correction for selection; 0.825 in 2018 versus 0.948 in 2017 for the model with correction).

4.3 Quantile Effects of Cash Holdings

Finally, we consider that the mean log-cash estimates are affected by the observed distributions having a heavy right tail for Bitcoin owners and being multimodal for non-owners—therefore we focus our attention on the quantiles of cash holdings. To investigate the

[19] One advantage of a CF approach is that it allows for a simple endogeneity test via a Wald test. In particular, we reject a null test of exogeneity of Bitcoin ownership, as we obtain a p-value for the Wald test of 0.

Table 6. Cash Holdings Estimates Modeled by Using OLS; OLS with CF; Q50 with CF

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Own Bitcoin	1.362***	0.948***	0.907***	1.179***	0.825***	1.052***
	(0.203)	(0.211)	(0.195)	(0.230)	(0.239)	(0.265)
Respondent Age	0.0185***	0.0244***	0.0210***	0.0114***	0.0165***	0.0192***
	(0.00197)	(0.00219)	(0.00257)	(0.00273)	(0.00296)	(0.00342)
Gender: Female	–0.271***	–0.127**	–0.195***	–0.393***	–0.290***	–0.351***
	(0.0609)	(0.0621)	(0.0718)	(0.0765)	(0.0783)	(0.0912)
Income: 50k–99k	0.244***	0.258***	0.263***	0.251***	0.167**	0.270***
	(0.0679)	(0.0690)	(0.0793)	(0.0798)	(0.0810)	(0.0921)
Income: 100k+	0.511***	0.552***	0.567***	0.455***	0.371***	0.420***
	(0.0866)	(0.0866)	(0.0977)	(0.110)	(0.107)	(0.132)
Prairies	0.125	0.216**	0.216*	0.0498	0.0750	0.110
	(0.103)	(0.0979)	(0.121)	(0.134)	(0.139)	(0.166)
Ontario	0.0940	0.156*	0.151	0.0134	0.0485	0.0994
	(0.0863)	(0.0850)	(0.0963)	(0.104)	(0.107)	(0.115)
Quebec	0.142	0.200**	0.187	–0.0301	0.0328	0.0565
	(0.0949)	(0.0926)	(0.119)	(0.110)	(0.118)	(0.124)
Atlantic	0.0434	0.147	0.107	–0.117	–0.0635	–0.123
	(0.129)	(0.130)	(0.134)	(0.174)	(0.171)	(0.167)
Employment	0.0419	–0.000747	–0.0690	–0.000752	0.00125	–0.0340
	(0.0630)	(0.0635)	(0.0738)	(0.0760)	(0.0737)	(0.0819)
College/CEGEP/Trade School	–0.0337	–0.0154	0.0592	–0.0374	–0.0736	0.0412
	(0.0780)	(0.0810)	(0.0979)	(0.0957)	(0.0965)	(0.103)
University	0.0843	0.0515	0.111	0.231**	0.163*	0.301***
	(0.0775)	(0.0799)	(0.0964)	(0.0988)	(0.0927)	(0.105)

(*continued*)

Table 6. (Continued)

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Number of Kids:	–0.0445	–0.000459	0.00768	–0.118	–0.00573	0.0138
No Kids	(0.0749)	(0.0743)	(0.0835)	(0.101)	(0.101)	(0.110)
Marital Status:	0.00622	0.0435	0.0831	0.0958	0.134	0.142
Not Married/CL	(0.0690)	(0.0679)	(0.0759)	(0.0968)	(0.0924)	(0.102)
Grocery Shopping:	–0.174***	–0.0963	–0.112	–0.168**	–0.0907	–0.250***
Not All of It	(0.0631)	(0.0642)	(0.0744)	(0.0854)	(0.0816)	(0.0927)
$\widehat{\epsilon_i}$		3.067***	1.914***		2.716***	1.550**
		(0.524)	(0.556)		(0.560)	(0.788)
Constant	2.481***	1.877***	2.212***	3.098***	2.581***	2.516***
	(0.167)	(0.196)	(0.231)	(0.235)	(0.250)	(0.281)
Observations	2,623	2,623	2,623	1,987	1,987	1,987
R-squared	0.089	0.108		0.080	0.093	

Note: Column 1 is for benchmark OLS model for year 2017; column 2 is OLS with CF correction for year 2017; column 3 is the median model with CF correction for year 2017. Columns 4, 5, and 6 are symmetrical models for year 2018. Baseline categories are male, <50k income, British Columbia region, unemployment, high school education, have children, married, and conducts all household grocery shopping. $\widehat{\epsilon_i}$ is the control function (CF). ***, **, and * represent 1 percent, 5 percent, and 10 percent significance, respectively. Bootstrap standard errors are in parentheses.

effects of Bitcoin ownership across the distribution, we first estimate benchmark quantile models allowing us to test H_{02}. Then we introduce the CF correction term (as in the linear case) so that we can test H'_{02}. The results of the conditional quantile model without selection (benchmark) for 2017 and 2018 are presented in Table 7 and Table 8; results correcting for endogenous selection via the CF term are presented in Table 9 and Table 10.

Given the observed distribution of log-cash for Bitcoin owners and non-owners, we would expect the median estimate to be below the estimated mean effect (at least in 2017), the lower quantile effects to be insignificant, and the higher quantile effects to be strongly in favor of Bitcoin owners. Indeed, for the year 2017 the estimated median effect (estimated at 0.907) of Bitcoin ownership on log cash is below the conditional mean effect estimated at 0.948. The pattern across quantiles in the benchmark quantile model is not monotonically increasing as expected, with higher estimated values at lower quantiles than expected.

For 2018 we observe four differences: at lower quantiles the estimated cash holdings are not significant between Bitcoin owners and non-owners; the median is higher than the median estimate from 2017 by about 30 percent; the high quantiles of cash are lower than in 2017, as we see a bigger bending down at the highest quantiles;[20] and there is a change in significance for gender and age at high quantiles of cash (gender remains significant while age becomes insignificant). These changes can be explained by the observed changes in demographics for Bitcoin owners in 2018.

As in the linear case with correction for selection, the results emphasize that indeed the estimated conditional median effect is smaller (estimated at 0.907 for 2017 and 1.052 for 2018) than the one obtained using the benchmark quantile estimates and the unconditional median. Once we control for selection, the conditional quantiles show the expected patterns: no significant effects at lower quantiles and an increased difference in cash holdings between Bitcoin owners and non-owners over the quantiles up the 90 percentile, with a correction down at the 95 percentile.

[20]The difference in cash holdings between the lower and higher quantiles is, however, larger in 2018 versus 2017.

Table 7. Quantiles of Cash Holdings, 2017

Variables	(1) Q10_2017	(2) Q25_2017	(3) Q50_2017	(4) Q75_2017	(5) Q90_2017	(6) Q95_2017
Own Bitcoin	0.874*	1.063***	1.038***	1.654***	2.629***	3.051***
	(0.461)	(0.238)	(0.244)	(0.444)	(0.405)	(0.433)
Respondent Age	0.0261***	0.0304***	0.0169***	0.0156***	0.0170***	0.0134***
	(0.00458)	(0.00353)	(0.00238)	(0.00238)	(0.00347)	(0.00422)
Gender: Female	0.0400	–0.282***	–0.293***	–0.301***	–0.455***	–0.350***
	(0.129)	(0.101)	(0.0655)	(0.0699)	(0.104)	(0.121)
Income: 50k–99k	0.0981	0.312***	0.287***	0.210***	0.366***	0.347***
	(0.152)	(0.115)	(0.0757)	(0.0763)	(0.116)	(0.133)
Income: 100k+	0.559***	0.574***	0.572***	0.403***	0.588***	0.493***
	(0.193)	(0.136)	(0.0978)	(0.0949)	(0.130)	(0.187)
Prairies	0.248	0.123	0.155	0.0489	0.227	0.237
	(0.236)	(0.205)	(0.114)	(0.111)	(0.157)	(0.171)
Ontario	0.169	0.145	0.152*	–0.0389	–0.0536	–0.100
	(0.225)	(0.162)	(0.0903)	(0.0959)	(0.133)	(0.153)
Quebec	0.286	0.154	0.146	0.0312	–0.0297	–0.110
	(0.258)	(0.159)	(0.113)	(0.101)	(0.144)	(0.173)
Atlantic	–0.0714	0.142	0.0835	–0.122	0.324	0.294
	(0.258)	(0.251)	(0.126)	(0.170)	(0.216)	(0.288)
Employment	0.115	–0.0178	–0.0607	0.0684	0.130	0.214*
	(0.137)	(0.117)	(0.0724)	(0.0690)	(0.109)	(0.124)
College/CEGEP/Trade School	–0.0868	–0.0376	0.0413	–0.0494	–0.211	–0.0306
	(0.158)	(0.132)	(0.0943)	(0.0855)	(0.147)	(0.158)
University	0.0662	0.0913	0.132	0.0684	–0.116	0.0331
	(0.157)	(0.135)	(0.0942)	(0.0875)	(0.132)	(0.129)

(*continued*)

Table 7. (Continued)

Variables	**(1) Q10_2017**	**(2) Q25_2017**	**(3) Q50_2017**	**(4) Q75_2017**	**(5) Q90_2017**	**(6) Q95_2017**
Number of Kids: No Kids	0.133	–0.144	–0.0343	–0.0314	–0.172	–0.153
	(0.148)	(0.131)	(0.0831)	(0.0800)	(0.118)	(0.157)
Marital Status:	–0.116	0.0786	0.0590	0.0327	0.132	0.0808
Not Married/CL	(0.132)	(0.119)	(0.0753)	(0.0842)	(0.103)	(0.137)
Grocery Shopping:	–0.155	–0.174*	–0.156**	–0.122	–0.0564	–0.0864
Not All of It	(0.141)	(0.104)	(0.0735)	(0.0776)	(0.0958)	(0.122)
Constant	–0.340	1.062***	2.598***	3.662***	4.414***	4.857***
	(0.364)	(0.324)	(0.200)	(0.197)	(0.303)	(0.330)
Observations	2,623	2,623	2,623	2,623	2,623	2,623

Note: Baseline categories are male, <50k income, British Columbia region, unemployment, high school education, have children, married, and conducts all household grocery shopping. ***, **, and * represent 1 percent, 5 percent, and 10 percent significance, respectively. Bootstrap standard errors are in parentheses.

Table 8. Quantiles of Cash Holdings, 2018

Variables	(1) Q10_2018	(2) Q25_2018	(3) Q50_2018	(4) Q75_2018	(5) Q90_2018	(6) Q95_2018
Own Bitcoin	0.422	0.459	1.314***	1.367***	2.811***	2.642***
	(0.432)	(0.433)	(0.210)	(0.308)	(0.664)	(0.354)
Respondent Age	0.0235***	0.0226***	0.0155***	0.00818**	–4.05e-05	–0.00472
	(0.00624)	(0.00415)	(0.00285)	(0.00376)	(0.00423)	(0.00640)
Gender: Female	0.0717	–0.351***	–0.372***	–0.474***	–0.535***	–0.608***
	(0.172)	(0.116)	(0.0835)	(0.0910)	(0.110)	(0.199)
Income: 50k–99k	0.284	0.424***	0.331***	0.216**	0.143	–0.00868
	(0.211)	(0.124)	(0.0814)	(0.0999)	(0.122)	(0.178)
Income: 100k+	0.415	0.570***	0.466***	0.488***	0.368**	0.212
	(0.277)	(0.157)	(0.122)	(0.140)	(0.174)	(0.243)
Prairies	–0.483	–0.270	0.0602	0.339**	0.331	0.315
	(0.306)	(0.179)	(0.165)	(0.156)	(0.208)	(0.252)
Ontario	–0.127	–0.0494	0.0838	0.101	0.0488	–0.102
	(0.308)	(0.138)	(0.114)	(0.121)	(0.174)	(0.201)
Quebec	–0.0809	–0.153	0.0509	0.0724	–0.168	–0.200
	(0.344)	(0.155)	(0.125)	(0.122)	(0.191)	(0.262)
Atlantic	–0.379	–0.600*	–0.144	–0.0580	0.0271	0.183
	(0.345)	(0.317)	(0.160)	(0.223)	(0.365)	(0.504)
Employment	0.0199	0.0215	–0.0602	–0.0936	0.0383	0.0758
	(0.177)	(0.114)	(0.0819)	(0.0931)	(0.124)	(0.178)
College/CEGEP/Trade School	–0.0108	–0.0753	0.0569	0.0529	0.114	–0.0426
	(0.196)	(0.164)	(0.101)	(0.112)	(0.164)	(0.245)
University	0.442**	0.215	0.320***	0.268**	0.202	–0.0473
	(0.217)	(0.156)	(0.105)	(0.119)	(0.165)	(0.217)

(continued)

Table 8. (Continued)

Variables	**(1) Q10_2018**	**(2) Q25_2018**	**(3) Q50_2018**	**(4) Q75_2018**	**(5) Q90_2018**	**(6) Q95_2018**
Number of Kids: No Kids	–0.0634	–0.174	–0.0401	–0.0774	0.0895	–0.147
	(0.210)	(0.155)	(0.104)	(0.138)	(0.165)	(0.263)
Marital Status:	0.219	0.296**	0.110	0.0265	–0.107	–0.0778
Not Married/CL	(0.185)	(0.143)	(0.0973)	(0.125)	(0.125)	(0.181)
Grocery Shopping:	0.183	–0.132	–0.321***	–0.230**	–0.123	–0.113
Not All of It	(0.156)	(0.130)	(0.0919)	(0.109)	(0.119)	(0.169)
Constant	–0.144	1.623***	2.846***	4.203***	5.339***	6.615***
	(0.548)	(0.338)	(0.251)	(0.302)	(0.372)	(0.523)
Observations	1,987	1,987	1,987	1,987	1,987	1,987

Note: Baseline categories are male, <50k income, British Columbia region, unemployment, high school education, have children, married, and conducts all household grocery shopping. ***, **, and * represent 1 percent, 5 percent, and 10 percent significance, respectively. Bootstrap standard errors are in parentheses.

Table 9. Quantiles of Cash Holdings, 2017: Corrected for Selection via a Control Function

Variables	(1) Q10CF_2017	(2) Q25CF_2017	(3) Q50CF_2017	(4) Q75CF_2017	(5) Q90CF_2017	(6) Q95CF_2017
Own Bitcoin	0.257	0.634***	0.907***	1.150***	1.960***	1.759***
	(0.435)	(0.226)	(0.195)	(0.357)	(0.465)	(0.598)
Respondent Age	0.0351***	0.0355***	0.0210***	0.0196***	0.0202***	0.0168***
	(0.00484)	(0.00369)	(0.00257)	(0.00258)	(0.00351)	(0.00452)
Gender: Female	0.234*	–0.189*	–0.195***	–0.187**	–0.266**	–0.208*
	(0.134)	(0.101)	(0.0718)	(0.0730)	(0.105)	(0.126)
Income: 50k–99k	0.234	0.312***	0.263***	0.226***	0.347***	0.324**
	(0.149)	(0.113)	(0.0793)	(0.0763)	(0.120)	(0.136)
Income: 100k+	0.665***	0.602***	0.567***	0.444***	0.538***	0.533***
	(0.197)	(0.129)	(0.0977)	(0.0997)	(0.129)	(0.196)
Prairies	0.358*	0.146	0.216*	0.0708	0.206	0.275
	(0.205)	(0.190)	(0.121)	(0.119)	(0.149)	(0.188)
Ontario	0.134	0.168	0.151	0.0184	0.0192	–0.0168
	(0.200)	(0.143)	(0.0963)	(0.0987)	(0.131)	(0.160)
Quebec	0.316	0.165	0.187	0.0674	0.0179	0.0359
	(0.231)	(0.143)	(0.119)	(0.102)	(0.150)	(0.183)
Atlantic	–0.0177	0.218	0.107	–0.0250	0.309	0.508
	(0.234)	(0.236)	(0.134)	(0.173)	(0.217)	(0.316)
Employment	0.0272	–0.0441	–0.0690	0.0681	–0.0143	0.145
	(0.139)	(0.116)	(0.0738)	(0.0713)	(0.105)	(0.133)
College/CEGEP/ Trade School	–0.0120	0.00606	0.0592	–0.0301	–0.154	–0.0315
	(0.159)	(0.138)	(0.0979)	(0.0858)	(0.145)	(0.161)
University	0.0579	0.0974	0.111	0.0540	–0.122	–0.0815
	(0.149)	(0.135)	(0.0964)	(0.0901)	(0.133)	(0.142)

(*continued*)

Table 9. (Continued)

Variables	**(1) Q10CF_2017**	**(2) Q25CF_2017**	**(3) Q50CF_2017**	**(4) Q75CF_2017**	**(5) Q90CF_2017**	**(6) Q95CF_2017**
Number of Kids:						
No Kids	0.160	–0.142	0.00768	0.0237	–0.0954	–0.115
	(0.142)	(0.137)	(0.0835)	(0.0811)	(0.131)	(0.159)
Marital Status:						
Not Married/CL	–0.0730	0.0505	0.0831	0.0525	0.133	0.229
	(0.144)	(0.113)	(0.0759)	(0.0827)	(0.107)	(0.144)
Grocery Shopping:						
Not All of It	–0.178	–0.127	–0.112	–0.0479	–0.0142	0.0361
	(0.148)	(0.104)	(0.0744)	(0.0759)	(0.0974)	(0.134)
$\widehat{\epsilon_i}$	4.068***	3.216***	1.914***	2.539***	3.002***	3.753**
	(0.951)	(0.613)	(0.556)	(0.611)	(1.164)	(1.600)
Constant	–1.078***	0.631*	2.212***	3.178***	4.020***	4.379***
	(0.411)	(0.340)	(0.231)	(0.220)	(0.334)	(0.397)
Observations	2,623	2,623	2,623	2,623	2,623	2,623

Note: Baseline categories are male, <50k income, British Columbia region, unemployment, high school education, have children, married, and conducts all household grocery shopping. $\widehat{\epsilon_i}$ is the CF. ***, **, and * represent 1 percent, 5 percent, and 10 percent significance, respectively. Bootstrap standard errors are in parentheses.

Table 10. Quantiles of Cash Holdings, 2018: Corrected for Selection via a Control Function

Variables	(1) Q10CF_2018	(2) Q25CF_2018	(3) Q50CF_2018	(4) Q75CF_2018	(5) Q90CF_2018	(6) Q95CF_2018
Own Bitcoin	0.0916	0.387	1.052***	1.094***	2.485***	2.029***
	(0.388)	(0.366)	(0.280)	(0.280)	(0.800)	(0.782)
Respondent Age	0.0261***	0.0258***	0.0192***	0.0113***	0.00307	–0.000224
	(0.00616)	(0.00430)	(0.00344)	(0.00386)	(0.00462)	(0.00581)
Gender: Female	0.0407	–0.199*	–0.351***	–0.381***	–0.468***	–0.668***
	(0.166)	(0.117)	(0.0865)	(0.0946)	(0.118)	(0.166)
Income: 50k–99k	0.174	0.385***	0.270***	0.185*	0.124	–0.113
	(0.199)	(0.130)	(0.0924)	(0.100)	(0.132)	(0.176)
Income: 100k+	0.356	0.516***	0.420***	0.416***	0.361**	0.0454
	(0.243)	(0.155)	(0.135)	(0.133)	(0.176)	(0.229)
Prairies	–0.202	–0.294	0.110	0.441***	0.420*	0.350
	(0.323)	(0.198)	(0.167)	(0.156)	(0.226)	(0.263)
Ontario	0.126	–0.0504	0.0994	0.125	0.147	0.115
	(0.328)	(0.139)	(0.115)	(0.122)	(0.187)	(0.197)
Quebec	0.123	–0.126	0.0565	0.145	–0.0890	0.107
	(0.343)	(0.164)	(0.127)	(0.127)	(0.198)	(0.256)
Atlantic	–0.0870	–0.593**	–0.123	–0.0749	0.131	0.378
	(0.358)	(0.273)	(0.171)	(0.195)	(0.385)	(0.422)
Employment	0.0281	0.0174	–0.0340	–0.104	–0.0185	0.179
	(0.167)	(0.117)	(0.0805)	(0.101)	(0.127)	(0.162)
College/CEGEP/ Trade School	–0.0989	–0.0584	0.0412	0.0164	0.0316	–0.205
	(0.193)	(0.167)	(0.103)	(0.107)	(0.167)	(0.235)
University	0.276	0.179	0.301***	0.254**	0.0735	–0.189
	(0.212)	(0.151)	(0.106)	(0.118)	(0.165)	(0.208)

(*continued*)

Table 10. (Continued)

Variables	**(1) Q10CF_2018**	**(2) Q25CF_2018**	**(3) Q50CF_2018**	**(4) Q75CF_2018**	**(5) Q90CF_2018**	**(6) Q95CF_2018**
Number of Kids:	0.0805	–0.137	0.0138	0.0478	0.150	0.315
No Kids	(0.195)	(0.167)	(0.116)	(0.135)	(0.170)	(0.280)
Marital Status:	0.207	0.347**	0.142	0.0293	–0.0738	–0.0281
Not Married/CL	(0.175)	(0.145)	(0.101)	(0.126)	(0.130)	(0.166)
Grocery Shopping:	0.258*	–0.0813	–0.250**	–0.151	–0.0901	–0.0436
Not All of It	(0.156)	(0.129)	(0.0995)	(0.118)	(0.128)	(0.177)
$\widehat{\epsilon}_i$	3.546***	2.021**	1.550**	2.011***	1.873	4.009
	(0.819)	(0.802)	(0.790)	(0.655)	(1.518)	(2.694)
Constant	–0.646	1.236***	2.516***	3.793***	5.044***	5.774***
	(0.566)	(0.370)	(0.289)	(0.337)	(0.391)	(0.527)
Observations	1,987	1,987	1,987	1,987	1,987	1,987

Note: Baseline categories are male, <50k income, British Columbia region, unemployment, high school education, have children, married, and conducts all household grocery shopping. $\widehat{\epsilon}_i$ is the CF. ***, **, and * represent 1 percent, 5 percent, and 10 percent significance, respectively. Bootstrap standard errors are in parentheses.

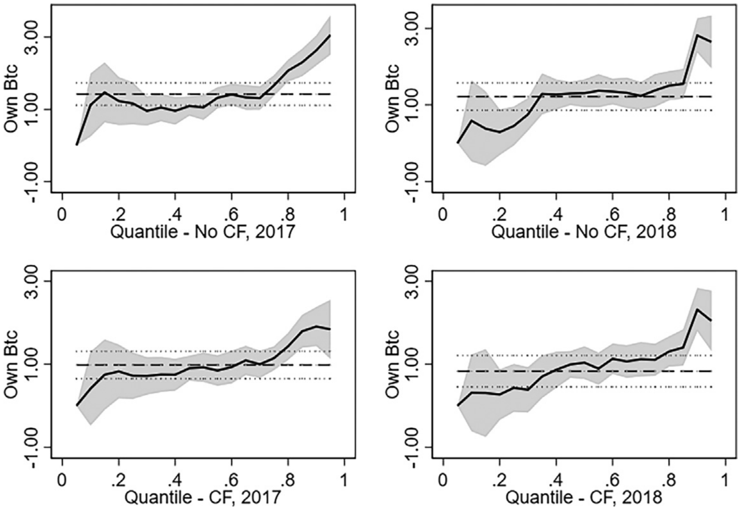
The demographic characteristics that are relevant for the linear model are also relevant for the quantile model, however there are differences between the 2017 and 2018 quantile results. For 2017, age has a positive effect, with a marginal effect that varies across quantiles; gender-female has a negative effect, with marginal effects that are higher at lower quantiles and lower at high quantiles of cash; at the 95 percentile, gender cash holdings differences become insignificant; and higher-income categories show positive effects over the benchmark category (0 to CAN$50,000), an effect that is maintained across all quantiles. For 2018, age, while positive and significant at quantiles of cash below 90, becomes insignificant at high quantiles of cash; the female dummy remains significant across all quantiles of cash and increases in relevance at high quantiles; and the income effects become insignificant at high quantiles of cash. The observed changes of the impact of demographic characteristics on cash holdings between the 2017 and 2018 surveys are driven by the observed distributional changes in the demographics of Bitcoin owners who are more gender balanced, older, more educated, and have higher income in 2018 when compared to 2017.

A graphical representation of the differences between the benchmark quantiles estimates and the corrected for selection quantile estimates is presented in Figure 4. The results show how selection affects the quantile estimates, especially the lowest and the highest ones.

5. Discussion and Conclusion

The year 2017 was significant in the evolution of cryptocurrencies. As the price of Bitcoin skyrocketed, these instruments garnered increased popular interest along with scrutiny from regulatory bodies and the financial sector. This was followed by a steep decline in the price of Bitcoin over the course of 2018, bottoming out in early 2019. Against this background, much of the discussion on Bitcoin came down to how people were actually using it: Was it a vehicle for speculation or a legitimate investment? Or, a convenient way for criminals to transact online? Were people using Bitcoin as it was originally designed—that is, a decentralized currency providing new avenues for transactions that would otherwise not have taken place? The answers to these questions are still largely unclear even

Figure 4. Predictive Quantiles of the Difference in Cash Holdings (in logs) between Bitcoin Owners and Non-owners



Note: The panels plot the predicted margins for the quantiles of the difference in cash holdings (in logs) between Bitcoin owners and non-owners. The top graphs plot the predicted quantiles when we do not account for the endogenous selection for 2017 (top left) and 2018 (top right). The bottom graphs plot the predicted quantiles when we account for the endogenous selection for 2017 (bottom left) and 2018 (bottom right).

now, but they have become increasingly relevant via-à-vis proposals for central bank digital currency and the decline of cash use for payments.

Using data from the Bank of Canada's 2017 and 2018 Bitcoin Omnibus Survey, this paper sheds light on a surprising finding that illustrates how digital currencies are playing a role in supplementing existing payment methods and financial systems. Controlling for observable factors and—most importantly—selection into Bitcoin ownership, we show that the cash holdings of Bitcoin owners are substantially higher than for non-owners. Further, this difference is most drastic among consumers who hold large amounts of cash.

Our analysis raises further questions about the specific factors driving Bitcoin owners to hold more cash, as well as the relative importance of such factors. It is clear that there are limitations to our data set. From the perspective of Bitcoin as an investment vehicle, for example, Fujiki (2020) uses Japanese survey data containing information about other financial asset holdings (stocks, bonds, etc.), in addition to Bitcoin ownership. Such details about other financial holdings, or the characteristics of consumers acting as investors (e.g., their risk preferences) are not available in the BTCOS. Fujiki (2020) finds that Bitcoin owners may be using cash to serve as a hedge for a relatively larger share of conventional risky assets in their overall portfolio. More recently, Balutel, Engert, et al. (2022) document how a broad increase in overall savings and investment during the COVID-19 pandemic translated to increased Bitcoin ownership in Canada. These more recent Bitcoin investors, who adopted in 2020 and 2021, still hold more cash, but relatively less so than Bitcoin owners in 2017–18.

From a payments perspective, Stix (2021) documents survey evidence from Austria showing that beliefs about the future use of Bitcoin may be relevant.[21] Specifically, while Bitcoin owners are extremely confident about the advantages of Bitcoin compared with conventional payment methods, only about half of them have actually used it to make a payment. In other words, while Bitcoin owners currently have a preference for cash, they may shift to using Bitcoin for payments in the event that it is more widely accepted in the future, to reduce the shoe-leather cost of holding cash. Data from 2015 show that the level of merchant acceptance of Bitcoin in Canada is quite low, at just 2 percent (see Fung, Huynh, and Kosse 2017). Huynh, Schmidt-Dengler, and Stix (2014) show that the transactional demand for cash is higher in areas of low payment card acceptance, as consumers face a higher probability of encountering transactions where cards are not accepted. A similar argument would apply to Bitcoin, but to a greater extent since Bitcoin acceptance is so rare.

Finally, we know from other data sources that Bitcoin owners and high cash holders do share commonalities that go beyond the observable characteristics measured by the BTCOS. For example, the Bank of Canada's 2017 Methods-of-Payment survey shows

[21] See also Balutel, Henry, et al. (2022) on the importance of beliefs about the future and the role of network effects in Bitcoin adoption.

that young males in general hold high amounts of cash for various reasons—they tend to have less access to credit cards, be more likely to be paid in cash by their employer, or have received cash transfers from their friends or family. See Henry, Huynh, and Welte (2018). As this younger population ages and becomes more integrated into the existing financial systems, their use and demand for both cash and Bitcoin may change.

To build on the work in this paper, we suggest several directions for future research. First, it is necessary to identify the specific features that Bitcoin owners deem relevant for determining its adoption and usage. Second, it would be useful to classify Bitcoin owners into various types, such as investors, casual users, etc. It is reasonable to assume that Bitcoin owners themselves are heterogeneous, and this needs to be factored into any analysis that attempts to explain the relationship between Bitcoin ownership and cash holdings. Finally, it would be useful to examine evidence from other countries, in particular developing countries. Canada may be considered relatively advanced in terms of financial inclusion and the structure of its financial system—how would results differ in countries where this is not the case?

Appendix

Table A.1. First Stage: Robustness (use of penalized likelihood to account for rare events)

Variables	(1) 2017: Logit	(2) 2017: Penalized Logit	(3) 2018: Logit	(4) 2018: Penalized Logit
Respondent Age	−0.0563***	−0.0551***	−0.0363***	−0.0355***
	(0.00944)	(0.00924)	(0.0116)	(0.00970)
Gender: Female	−1.357***	−1.325***	−0.802***	−0.782***
	(0.222)	(0.228)	(0.238)	(0.236)
Income: 50k–99k	−0.110	−0.106	1.018***	0.987***
	(0.265)	(0.253)	(0.311)	(0.304)
Income: 100k+	−0.353	−0.340	0.908**	0.882**
	(0.311)	(0.322)	(0.374)	(0.355)
Prairies	−0.818**	−0.799**	−0.0359	−0.0380
	(0.361)	(0.348)	(0.382)	(0.396)
Ontario	−0.558*	−0.554*	−0.292	−0.303
	(0.298)	(0.299)	(0.335)	(0.339)
Quebec	−0.610**	−0.605*	−0.459	−0.458
	(0.311)	(0.318)	(0.384)	(0.382)
Atlantic	−0.931**	−0.874*	−0.501	−0.438
	(0.458)	(0.460)	(0.609)	(0.560)
Employment	0.623**	0.594**	0.173	0.155
	(0.307)	(0.287)	(0.286)	(0.294)

(*continued*)

Table A.1. (Continued)

Variables	(1) 2017: Logit	(2) 2017: Penalized Logit	(3) 2018: Logit	(4) 2018: Penalized Logit
College/CEGEP/Trade School	0.0834	0.0757	0.911**	0.853**
	(0.321)	(0.316)	(0.423)	(0.405)
University	0.494	0.472	0.971**	0.908**
	(0.302)	(0.301)	(0.414)	(0.397)
Number of Kids: No Kids	–0.296	–0.291	–0.608**	–0.595**
	(0.234)	(0.243)	(0.271)	(0.269)
Marital Status: Not Married/CL	–0.196	–0.192	0.00200	0.00269
	(0.257)	(0.259)	(0.291)	(0.292)
Grocery Shopping: Not All of It	–0.275	–0.265	–0.242	–0.232
	(0.229)	(0.231)	(0.241)	(0.243)
EAR15	0.0405***	0.0397***	0.0378***	0.0369***
	(0.00433)	(0.00446)	(0.00538)	(0.00479)
Constant	–1.671**	–1.607**	–3.348***	–3.195***
	(0.658)	(0.644)	(0.943)	(0.829)
Observations	2,623	2,623	1,987	1,987

Note: Column 1 shows the results for the probability of ownership (column 2 in Table 4) for year 2017; column 2 is the equivalent penalized likelihood results for year 2017 that accounts for rare events; column 3 shows the results for the probability of ownership (column 6 in Table 4) for year 2018; column 4 is the equivalent penalized likelihood results for year 2018 that accounts for rare events. Baseline categories are male, <50k income, from British Columbia, unemployed, conducts all household grocery shopping, low financial knowledge. ***, **, and * represent 1 percent, 5 percent, and 10 percent significance, respectively.

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Model Risk at Central Counterparties: Is Skin in the Game a Game Changer?*

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As central counterparties (CCPs) have become systemic, their credit risk modeling has become critical for the global financial system. This paper empirically investigates CCPs' incentives to model credit risk. Our hypothesis is that the more CCPs stand to lose from mismanagement, the more conservatively they model credit risk. Accordingly, we find that the higher the skin in the game, i.e., the CCP capital dedicated to credit risk, the lower the model risk is. The results are significant and robust across different model risk proxies. Consistent with our hypothesis, the association with other forms of capital is not significant. Our findings inform the policy debate on CCP capital regulation.

JEL Codes: F34, F42, G21, G38.

1. Introduction

Central counterparties (CCPs) have become systemic players in over-the-counter (OTC) derivatives markets. A CCP stands between clearing member banks: each bank faces the CCP as its counterparty.

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This provides transparency. For instance, during the Lehman bankruptcy, CCPs unwound derivatives trades fast, while bilateral trades took years to resolve. This impressed regulators, who mandated central clearing for standardized OTC derivatives. Market forces, chiefly network externalities, amplified the regulatory drive for central clearing further. As a result, today almost four-fifths of interest rate derivatives and half of credit default swaps are cleared centrally through CCPs, up from one-third and one-tenth, respectively, in 2009 (Aramonte and Huang 2019). Furthermore, CCPs have become very concentrated, with just a handful of them dominating the major product lines (Huang and Takáts 2020). Thus, large CCPs have become systemically important.

One critical function of CCPs is to manage counterparty credit risk through margining (Faruqui, Huang, and Takáts 2018). By clearing a transaction, the CCP severs the bilateral link between banks and becomes the counterparty to each of them. While the derivative transaction has zero market value initially, its value changes with market movements. The bank that has incurred a mark-to-market loss has to post variation margin (VM) with the CCP (while the "winning" bank receives VM from the CCP). In order to manage the risk of potential non-payment of VM, the CCP requires banks to post initial margin (IM) to serve as collateral.

Model risk at CCPs is the risk of loss resulting from using insufficiently accurate IM models. For instance, Nasdaq Clearing almost failed in September 2018 due to undersizing IM. A single trader, Einar Aas, could not post VM, which far exceeded his IM. The resulting losses wiped out the CCP's capital that is dedicated to credit risk, the so-called skin in the game. Consequently, CCP members also had to bear significant losses (Bell and Holden 2018). Similar near-failure of large CCPs could disrupt the global financial system with systemic consequences.

Strikingly, given the systemic risks, managing model risk (i.e., right-sizing initial margin) is the sole responsibility of CCPs. The reason is that right-sizing IM requires expert judgment that outside parties, including regulators, do not fully possess. Right-sizing requires, among all else, correctly assessing future volatility, future correlations across various derivatives (and across other markets), the concentration of portfolios, and the time required to close failing portfolios amid severe market stress.[1] This information is not available for outsiders. Therefore, regulators rely on CCPs having the right incentives and provide only general guidelines for IM setting.

The question is, how well are CCP incentives aligned to manage model risk, i.e., to right-size initial margin? Surprisingly, there is a gap in the literature about how these incentives work in practice, despite the systemic importance of CCPs. In this paper we start to fill the gap.

We are the first to empirically investigate model risk and its relationship with CCP skin in the game (SITG), i.e., the specific element of CCP capital which is allocated to absorb credit risk. Our hypothesis is straightforward: the more the CCP stands to lose from mismanaging model risk, the more carefully it sets IM. Indeed, we find robust evidence that the higher the skin in the game, the lower the model risk is.

We collect data from quantitative disclosures of 39 CCP groups between 2015:Q3 and 2018:Q4. The data cover all internationally relevant CCPs. The 39 CCP groups have 120 separate CCP product lines. The collected data set contains information such as balance sheets, earnings, and the quality of credit risk management at the product line level.

Model risk at CCPs can be measured by back-testing IM models. IM is typically modeled as value-at-risk (VaR) of an expected loss distribution in which the loss is the non-payment of VM (see details in Section 3). The ex post performance of IM models is not directly observable through a single variable. Therefore we use five proxies of model risk from the quantitative disclosures: (1) number of margin breaches (i.e., how many times the VM exceeds the IM), (2) achieved coverage (i.e., what percentage of trades resulted in lower VM than IM), (3) difference between achieved coverage and target coverage (the latter being the targeted coverage ex ante from the model), (4) average size of margin breaches, and (5) maximum size of margin breaches.

[1]Closing concentrated derivative portfolios takes longer and can disrupt markets more, as the recent collapse of Archegos shows, for instance. Banks suffered losses over USD 10 billion from the failure of the relatively small firm, with Credit Suisse alone losing more than USD 5 billion (*Financial Times*, April 27, 2021).

We empirically test our hypothesis. We find that higher skin in the game is associated with lower model risk, consistent with our hypothesis. For instance, higher skin in the game is associated with less frequent margin breaches. The results are significant and robust across all five model risk proxies. Our results also support the auxiliary hypothesis: we do not find a similar significant relationship between model risk and CCP capital other than skin in the game (i.e., capital not exposed to credit risk).

Our results should be interpreted as being consistent with the theoretical arguments that higher SITG lowers model risk. Importantly, we do not determine causality unambiguously from the regression results themselves. Yet, our empirical evidence is consistent with the theoretical priors that higher SITG lowers model risk.

Our results are policy relevant. The results suggest that higher skin in the game incentivizes CCPs to reduce model risks. This matters for financial stability due to the systemic role CCPs play at the center of the financial system. This also matters for major clearing member banks and end users (such as asset managers), who face huge potential losses should major CCPs mismanage model risk on a large scale. In sum, the results suggest that policymakers might want to think about potential CCP capital requirements, especially as franchise value does not seem to incentivize CCPs strongly enough to manage model risk.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 briefly discusses how CCPs function. Section 4 introduces our hypotheses. Section 5 details our data set, and Section 6 discusses our proxies for model risk. Section 7 shows our analysis. Section 8 discusses robustness. The final section concludes with caveats and policy implications.

2. Literature Review

Our work contributes to two streams of literature. First, our work adds empirical evidence to the small but fast-growing literature on incentives and risks resulting from the mutualization of counterparty credit risk. Biais, Heider, and Hoerova (2012) highlight the diversification benefits from central clearing but warn of moral hazard in the case of fully insured credit risk. Biais, Heider, and Hoerova (2016) show, however, that margin requirements can prevent such moral hazard.[2] Carter and Garner (2015) and Saguato (2017) sketch the conceptual framework of CCP skin in the game. Huang (2019) develops this line of thinking towards our question by theoretically examining the link between CCP capitalization and risk-taking incentives.

Second, we complement the nascent literature that investigates CCP risk management empirically. In this area, Bignon and Vuillemey (2020) describe a high-profile central clearinghouse failure. The documentation of this rare failure is particularly relevant when thinking about potential triggers for failure. Huang (2019) focuses on the role of CCP skin in the game, including its association with the aggregate amount of collateral, i.e., initial margin (IM). We depart from Huang (2019) by focusing explicitly on the model risk of CCP credit risk management. Thus, instead of aggregate IM size, we look at the performance (i.e., the back-testing) of the margin models. The main reason is that a high aggregate amount of IM does not necessarily preclude CCP failures, because IM is not fungible across members. A member's IM can only cover risks from his own portfolio. For example, if NASDAQ Clearing had prescribed IM on trades other than those of Mr. Aas, it would not have safeguarded the CCP during the near failure.

Furthermore, analyzing model risk based on back-testing results as opposed to aggregate IM can help identification by excluding a confounding factor. Namely, a greater amount of skin in the game may induce clearing members to take more risks, because trades are safer due to the CCP's higher loss-absorbing capacity. Reflecting this higher risk-taking, the CCP might increase aggregate IM. This effect could confound estimates that aim to analyze the impact of skin in the game based on aggregate IM: it would remain unclear if higher skin in the game induces more risk-taking by members and thereby leads indirectly to higher aggregate IM, or if higher skin in the game increases the CCP's incentive to manage risks more conservatively, which raises aggregate IM. This issue is not present

[2]In addition, an entire school of papers is dedicated to investigate netting benefits (Duffie and Zhu 2011; Cont and Kokholm 2014; Duffie, Scheicher, and Vuillemey 2015). Several others examine how central clearing can alleviate OTC derivative market opacity: Acharya and Bisin (2009, 2014); Koeppl and Monnet (2010, 2013); Koeppl, Monnet, and Temzalides (2012).

in our approach based on back-testing results: model performance proxies already include the effects of increased risk-taking by members. Therefore, while we build on the argument in Huang (2019), we move from investigating aggregate initial margin to portfolio-specific initial margin and model risk.

3. Institutional Background

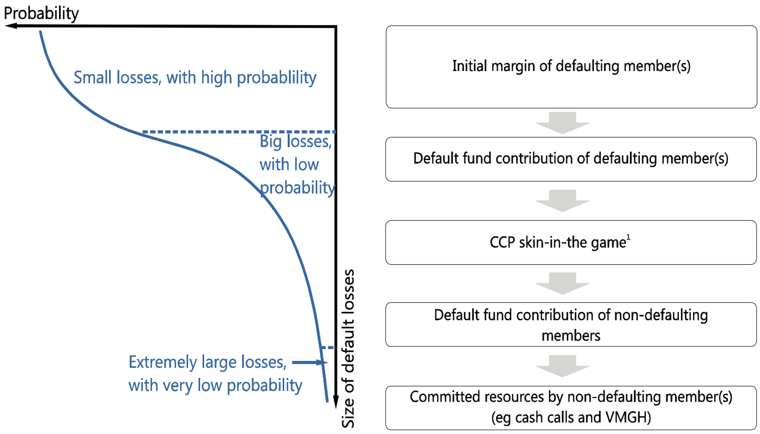
CCPs are financial market infrastructures that provide clearing services. CCPs essentially stand between two counterparties (for instance, banks) and assume the credit risk from the contracting parties. In this section, we briefly review how CCPs work. We focus on two features, which are particularly relevant for our argument. First, we outline how central clearing works—in particular, how CCPs manage counterparty credit risk through initial margin setting. Second, we discuss the special loss-absorbing setup of CCPs, called the default waterfall—in particular, the role of skin in the game.

3.1 Initial Margin Setting

As discussed in the introduction, the CCP severs the link between the contracting parties. The resulting counterparty credit risk is measures by setting trade-specific initial margin.

CCPs set IM to cover, with a high likelihood, the potential VM payments over a period long enough to close the failing positions even in stressed market conditions. Setting IM involves expert judgment. Typically, CCPs model IM as a value-at-risk measure, which is a quantile of the loss distribution (Pirrong 2011). Many CCPs target the 99th percentile, for instance. Another key determinant is the time expected to close a position: this tends to be longer in stressed market conditions and for concentrated positions. In addition, the precise IM setting involves expert judgment about correlations across different derivatives, the nature of stressed market conditions, and the behavior of concentrated exposures, among many other factors. Therefore, regulators provide only broad guidelines on IM setting.

Figure 1. Default Waterfall



Source: Faruqui, Huang, and Takáts (2018).
Note: The left-hand panel shows the default loss distribution and the right-hand panel shows the financial resources used in the default waterfall.

3.2 Default Waterfall

To withstand losses from the materialization of a counterparty credit risk event, CCPs rely on a range of resources through the so-called default waterfall (Faruqui, Huang, and Takáts 2018). In the event of a clearing member bank's default, a CCP first absorbs losses by drawing on the IM that the defaulting bank has posted (Figure 1).[3] Importantly, IM is not fungible across members: a bank's IM can only be used to cover its own losses, not other banks' losses (Wang, Capponi, and Zhang 2019).

If the defaulter's IM is insufficient, the CCP has access to the defaulting bank's contribution to the default fund. Banks need to contribute to the CCP's default fund in order to be able to trade with the CCP.

The next layer in the waterfall is the CCP capital dedicated to absorb credit risk, called "skin in the game." SITG is the layer that

[3]To ease exposition, we refer to members as banks in the following. While not all members are necessarily banks, many of the most important clearing members are indeed banks.

we focus on, because the risk of losing SITG might provide incentives for the CCP to manage risks prudently (Huang 2019). Importantly, CCPs have capital other than SITG. This other capital underwrites, for instance, operational risks. Critically from our perspective, unlike banks, CCPs do not have regulatory SITG requirements. This lack of minimum SITG requirement allows for heterogeneity in SITG across CCPs that we can utilize in our empirical investigations.[4]

Furthermore, CCPs also differ from banks in that they can continue as going concerns even after exhausting their SITG: they have other resources to absorb credit losses. First, CCPs can rely on member banks' prefunded resources, such as non-defaulting banks' default fund contributions. Second, CCPs can call on surviving banks to provide committed resources. Depending on the CCP rulebook, the CCP can call on the surviving members for more cash or can haircut the receivable VM payments owing to their winning positions (Singh 2014; Singh and Turing 2018).

Quantitatively, the overwhelming majority of CCPs' prefunded resources is IM (Figure 2, left-hand panel). Around 90 percent of all prefunded resources are IM (red area), and only around 10 percent are default fund contributions (yellow area). The SITG is dwarfed by IM and default fund contributions (indeed the blue area is so tiny that it is not visible on the figure). SITG amounts to only around USD 5 billion (center panel). In sum, CCP capital is very sparse, as compared with other collateral or with bank capital (right-hand panel).

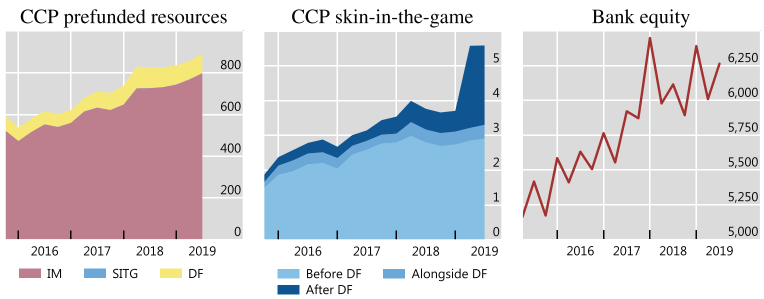
The data shows that SITG is small and could play a limited role in absorbing credit losses. Therefore, our inquiry focuses on its incentive role: that is, whether CCPs with higher SITG manage model risk more prudently.

4. Hypotheses

Exposing capital to losses encourages prudent behavior (Diamond and Rajan 2000; Hellmann, Murdock, and Stiglitz 2000). The evidence shows, for instance, that higher bank capital is associated

[4] The European Market Infrastructure Regulation (EMIR) requires that CCPs' SITG should be at least 25 percent of their operational capital. Such a requirement, however, is not a binding constraint for most CCPs.

Figure 2. CCP and Bank Resources (unit: USD bn)



Source: Clarus CCPview, Fitch.
Note: The left-hand panel shows the prefunded resources of CCPs. Skin in the game is not visible, because it is dwarfed by other prefunded resources. The central panel zooms in on the different layers of CCP SITG. The right-hand panel shows the equity of large banks. IM: initial margin; SITG: skin in the game; DF: default fund; Before DF: CCP skin in the game that will be used to absorb default losses before default fund being used; Alongside DF: CCP skin in the game that will be used together with default fund; After DF: CCP skin in the game that will be used after default fund.

with less risk-taking (Furlong and Keeley 1989): as shareholders stand to lose more if losses materialize, they are more prudent in terms of risk-taking. In the same vein, Huang (2019) provides a theoretical model and empirical evidence that a higher CCP SITG is associated with a higher aggregate IM.

In this paper, we depart from aggregate margin levels to look at margin model back-testing results. The reason is that a high aggregate amount of IM does not necessarily preclude CCP failures. Even if aggregate IM is high, the CCP remains exposed to the particular IM set for a particular trader's portfolio. In contrast to aggregate IM, the back-testing results identify whether CCPs right-sized portfolio-specific IM.

An additional advantage of using back-testing results is that it reduces a potential confounding factor arising from banks' risk-taking. Recall that according to the CCP default waterfall, default losses will be born by CCP skin in the game before depleting the members' default fund. Therefore, higher skin in the game makes banks less likely to face losses through their default fund. Lower default fund exposure, in turn, may induce banks to take more risks. This higher risk-taking, and the resulting higher risk of trades, might compel the CCP to increase aggregate IM. Thereby, the relationship between model performance and aggregate IM might also reflect banks' risk-taking. This effect can confound estimates on the relationship between SITG and CCPs' risk management, should one rely on aggregate IM.

This confounding factor, however, is not present in our approach. The reason is that our data shows the relationship between model performance and SITG after any changes in bank risk-taking and resulting CCP IM setting. The data, as the next section details, is essentially the back-testing of the risk model: for instance, it shows how often margin breaches arise. In short, we observe how the CCP risk model works after the CCP has adjusted its IM, including aggregate IM, for any changes in bank risk-taking. Hence, the above confounding effect (from higher risk-taking to higher IM) is not present when using back-testing results.

Therefore, we formulate our risk-taking hypotheses in terms of model back-testing results:

HYPOTHESIS 1. *A higher CCP skin in the game is associated with lower model risk as measured by model back-testing results.*

A related argument is that CCP capital other than SITG should not affect credit risk management. The reason is, as mentioned in Section 3: when a credit event happens, capital other than SITG is not exposed to credit losses. Therefore, such operating capital should not provide incentives for credit risk management. That leads to our next hypothesis.

HYPOTHESIS 2. *A higher amount of CCP operating capital is not significantly associated with model risk as measured by model back-testing results.*

We turn to our data to empirically test these two hypotheses.

5. Data

We use public CCP quantitative disclosures to test the two hypotheses. The CPMI-IOSCO Principles for Financial Market

Table 1. Summary Statistics

	Mean	**Std.**	**Min.**	**Median**	**Max.**
A. Default Waterfall					
Initial Margin (IM) ($bn)	9	19	0.0002	3	138.1
Skin in the Game (SITG) ($bn)	0.039	0.0595	0.00001	0.0164	0.272
Default Fund (DF) ($bn)	1.3	2.2	0.0002	0.3	15
B. Financial Information					
Return on Equity (ROE)	20%	27%	–29%	13%	169%
Profit ($m)	117.1	309.2	–14.46	51.9	4,063.4
Equity ($bn)	1.4	4.6	0.02	0.3	26
Other Equity ($bn)	1.4	4.6	0.01	0.2	25.8
Assets ($bn)	71.7	113.6	0.08	21.7	470.3

Source: CCP quantitative disclosures, Clarus CCPview, and authors' calculations.
Note: This table summarizes the financial variables. The summary statistics are taken across CCPs and quarters. The variables are divided into two groups: panel A reports the statistics for variables in CCP default waterfall. Panel B shows the balance sheet variables for CCPs. Note that Equity is the sum of SITG and Other Equity.

Infrastructures (PFMI) (CPMI-IOSCO 2012, 2015) require CCPs to publish them at a quarterly frequency. We use disclosure data collected by Clarus FT's CCPView.

Our data set is in panel form. The time series ranges from 2015:Q3 to 2018:Q4 at a quarterly frequency, i.e., 14 quarters. The data set spans 120 CCP entities or product lines (which are grouped into 39 CCP groups). Therefore, our data allow us to control for specific product lines. The full panel has at most 1,680 observations. We divide our data description into two categories (Table 1): (i) default waterfall (panel A) and (ii) financial information (panel B).[5]

Default waterfall data reveal that IM and default fund account for the majority of the default waterfall in our sample (Table 1, panel A). The average of IM at a given CCP entity is around USD 9 billion and that of the default fund is around USD 1.3 billion. Compared with IM and DF, SITG is small, with an average value of USD

[5]We discuss the third broad element, the model back-testing results, in the next section among the proxies for model risk management.

Table 2. Credit Risk Management

	Mean	Std.	Min.	Median	Max.
Number of Breaches	12.6	37.7	0	1	394
Number of Trades in Margin Model	148,492	1,038,522	239	13,154	14,148,135
Target Coverage (%)	99.2	0.3	99	99	99.9
Achieved Coverage (%)	99.9	0.03	96.17	100	100
Difference between Achieved and Target (%)	0.7	0.6	–8.96	0.9	1
Maximum Breach Size ($m)	61.6	130.1	0.01	7.2	1,228
Average Breach Size ($m)	4.7	9.1	0.01	1.4	67.1

Source: CCP quantitative disclosures, Clarus CCPview, and authors' calculations.
Note: This table summarizes the credit risk variables. The statistics are taken across CCPs and quarters.

40 million. These data are consistent with the CCP data discussed in the Institutional Background section. In addition, all three variables are heavily skewed to the right with median values far below the averages. Furthermore, all variables show high variation, with a standard deviation almost twice as large as the average. Importantly, the average CCP equity (i.e., the sum of skin in the game and other operational capital) is around USD 1.4 billion. Therefore, most CCP capital is operational capital and is not exposed to credit losses (Table 1, panel B).[6]

6. Proxies for Model Risk Management

CCP quantitative disclosures contain information on back-testing of CCPs' IM models (Table 2). The back-testing results show how carefully CCPs set individual, portfolio-specific IM to manage counterparty credit risk. Therefore, back-testing data allows us to test our hypotheses.

The back-testing results from quantitative disclosures inform us about portfolio-specific IM model performance through margin

[6]The financial information reveals high CCP profits. Return on equity (RoE) is 20 percent on average across entities in the sample period, with the maximum reaching 169 percent. Yet, in absolute value profits do not appear that high, as they average only around USD 117 million.

breaches. Recall that CCPs calculate IM as a value-at-risk measure and aim to achieve a quantile of an expected loss distribution. The targeted quantile is called the target coverage. The PFMI requires that CCPs should target at least 99 percent coverage (CPMI-IOSCO 2012). The 99 percent percentile target coverage implies that 99 percent of VM payments are aimed to be less than the required IM. As the target coverage is never 100 percent, some actual VM payments are expected to exceed the IM. In our example of 99 percent target coverage, 1 percent of VM is expected to exceed IM. These events are called margin breaches.

The back-testing results from quantitative disclosures provide information on margin breaches from five different perspectives:

- the number of breaches,
- achieved coverage,
- difference between achieved and target coverage,
- average size of margin breaches,
- maximum size of margin breaches.

First, the number of margin breaches is a straightforward metric of model risk. Controlling for CCP size, fewer margin breaches imply less model risk.

Second, achieved coverage scales margin breaches by the number of trades, as the following formula shows:

$$\begin{aligned}&\textit{Achieved coverage}\\&\quad = 1 - (\textit{Number of margin breaches})/(\textit{Number of trades}).\end{aligned}$$

Achieved coverage shows the proportion of trades that did not result in a margin breach. Its advantage over the numerical breach number is that it scales the number of breaches to the number of trades.

Third, the difference between achieved and target coverage shows how effective the CCP is at in reaching its own risk model target. Not all product lines and not all CCPs target the same coverage level. While the PFMI requires at least 99 percent coverage, most CCPs aim for a higher level. The difference proxy controls for these differences in targets.

Fourth, the average size of margin breaches informs about the potential losses that margin breaches could have affected. As an example, more frequent but smaller margin breaches might constitute less model risk than rarer but larger breaches.

Fifth and finally, the maximum size of margin breaches focuses our attention to the largest, and potentially most threatening, margin breach. As CCPs have a number of credit risk-absorbing layers, small breaches do not constitute a major risk—in contrast to large ones. The size difference is not trivial: the maximum breach in our sample reaches USD 1.3 billion, while the average margin breach hovers around USD 5 million.

All in all, these five proxies provide five different angles to consider model risk. None of them is perfect in isolation. However, taken together, especially when they point to a consistent picture, they provide useful information. Therefore, in our empirical analysis we consider all five proxies and look for consistent results across all five of them.

One advantage of the quantitative disclosure data is the large number of margin breach observations. Margin breaches might be rare relative to the number of trades, but the huge number of trades generates a steady stream of breaches for our empirical analysis. Therefore, we are able to deploy econometric tools to analyze all five above.

Importantly, the CCP quantitative disclosure data report the margin breaches for the past 12 months. Hence, the raw reported variables are autocorrelated. To address the autocorrelation, we use only the annual data of the size measures, i.e., the average size and the maximum size of margin breaches. For the frequency measures, it is possible to calculate the quarterly increment. We can calculate the quarterly number of margin breaches, which in turn allows us to calculate the achieved coverage and the difference between the achieved and the target coverage on a quarterly basis (see Appendix B for calculation details).

7. Regression Analysis

We test our hypotheses in a panel regression framework. Formally, we estimate

$$\begin{aligned} ModelRisk_{i,t} = \beta_0 + \beta_1 SITG_{i,t} + \beta_2 OtherEquity_{i,t} + \beta_3 Profit_{i,t} \\ + \gamma IMs_{i,t} + \delta Assets_{i,t} + \alpha_t + \iota_i + \varepsilon_{i,t}. \end{aligned} \quad (1)$$

Table 3. Regression Results with Skin in the Game

	Number of Breaches	Achieved Coverage	Diff. Coverage	Avg. Breach	Max. Breach
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
SITG	**–0.24**** **(–2.08)**	**0.07*** **(1.88)**	**0.09**** **(2.28)**	**–0.04*** **(–1.82)**	**–1.51*** **(–1.90)**
IM	–0.16 (–0.68)	–0.04 (–1.07)	0.01 (0.17)	–0.04 (–0.65)	–1.91** (–2.53)
Asset	–0.01 (–0.20)	0.01 (1.59)	0.01 (1.53)	0.00 (0.36)	–0.06 (–1.09)
Constant	45.65*** (8.32)	9,990.11*** (6,134.00)	140.73*** (65.80)	3.80*** (3.68)	108.13*** (3.35)
R-squared	0.008	0.003	0.000	0.012	0.095
N	557	557	557	168	168

Note: This table presents the regression results with skin in the game. The panel regressions incorporate the time and CCP entity fixed effects. t-statistics are in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Following the usual panel notation, index i stands for CCP entities (product lines) and t stands for quarters throughout.

Our dependent variable $ModelRisk_{i,t}$ denotes one of the five proxies defined in the previous section.

Our main explanatory variables stem from the two hypotheses we test: skin in the game and other equity. In addition, we control for profit, aggregate IM, and CCP assets in each quarter. Finally, we apply both entity and time fixed effects to capture unobserved CCP business line heterogeneity (such as ownership structure, governance, and product-specific features) and time-varying market conditions, respectively. Appendix A provides a summary of the variables used in regressions.

Our first set of regressions focuses on SITG (Table 3). We examine all five model risk proxies (see Models 1–5). Consistent with Hypothesis 1, we find that a higher SITG is associated with fewer breaches (Model 1), higher achieved coverage (Model 2), relatively higher difference between achieved and targeted coverage (Model 3), lower average (Model 4), and lower maximum size of margin breaches (Model 5). In short, all five proxies point consistently in the same direction: higher SITG is associated with lower model risk proxies, as Hypothesis 1 would suggest.[7]

Notice that our sample size drops for the average and maximum size proxies (Models 4 and 5). The reason is that here we have to use annual frequency data to avoid overlapping windows. Recall that CCPs are required to report model back-testing data over a 12-month period and it is only possible to uncover quarterly increments for number of breaches, achieved coverage, and the difference between average and target coverage.

Our second set of regressions extends our analysis to include other capital and profits (Table 4). Again, we consider all five proxies of model risk (Models 1–5).

The regressions confirm our first set of results about SITG: higher SITG continues to associate significantly with lower model risk across all five proxies even after controlling for other capital.

The regression results on other capital show a mixed picture—broadly consistent with our Hypothesis 2. The coefficient estimates on number of breaches (Model 1) and average breach size (Model 4) are insignificant. Achieved coverage (Model 2) and difference between achieved and targeted coverage (Model 3) show a negative relationship: higher other capital is associated with higher model risk across these two proxies. In contrast, maximum breach size (Model 5) suggests the exact opposite: higher other capital is associated with lower model risk. In short, no consistent picture emerges for capital other than SITG.

In sum, our results are strongly consistent with Hypothesis 1: a CCP with a higher SITG has smaller model risk for credit risk management, and hence more prudent risk management. The results also broadly support Hypothesis 2: there is no consistent, statistically significant relationship between other capital and CCP risk management. In the next section we examine the robustness of these results.

[7]One should be cautious about interpreting the regression results as direct causality. It is possible that CCPs with lower model risk are more willing to expose more capital to default losses, in order to signal their confidence in the IM models.

Table 4. Regression Results with SITG, Other Capital, and Profit

	Number of Breaches	Achieved Coverage	Diff. Coverage	Avg. Breach	Max. Breach
	(1)	(2)	(3)	(4)	(5)
SITG	**–0.24****	**0.07***	**0.09****	**–0.04***	**–1.51***
	(–2.07)	**(1.96)**	**(2.35)**	**(–1.81)**	**(–1.89)**
Other Capital	**1.16**	**–1.09*****	**–1.38*****	**–0.16**	**–1.91***
	(0.60)	**(–3.34)**	**(–3.54)**	**(–1.25)**	**(–1.79)**
Profit	0.00	–0.00	–0.00	–0.00	0.00
	(0.15)	(–1.45)	(–1.32)	(–0.23)	(0.09)
IM	–0.15	–0.05	0.01	–0.04	–1.92**
	(–0.66)	(–1.09)	(0.10)	(–0.66)	(–2.53)
Asset	–0.01	0.01*	0.01*	0.00	–0.06
	(–0.22)	(1.83)	(1.78)	(0.38)	(–1.06)
Constant	43.92***	9,992.18***	143.72***	4.03***	110.91***
	(6.29)	(5,119.94)	(63.79)	(3.63)	(3.32)
R-squared	0.008	0.010	0.000	0.012	0.095
N	557	557	557	168	168

Note: This table presents the regression results with skin in the game, other capital, and profit. The panel regressions incorporate the time and CCP entity fixed effects. t-statistics are in parentheses. *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01.

8. Robustness

We examine the robustness of our results in Table 3 and Table 4 along two directions. First, we investigate intermediate steps when extending the separate analysis of SITG to the joint triple investigation of SITG, other capital, and profits. In our main analysis, we introduced other capital and profits at once. Here, we add them separately. When we add only other capital to SITG in (Table C.1, in Appendix C) the results remain robust: higher SITG remains consistently associated with lower model risk, while no similar consistent association emerges for other capital. When we add only profits to SITG in (Table C.2, in Appendix C), we also observe results very similar to those in the main analysis: higher SITG remains consistently associated with lower model risk, while the association with profits remain consistently insignificant.

Second, we remove the controls for aggregate IM and CCP assets from our main specifications. We replicate the results of Table 3 without IM and asset controls (Table C.3, in Appendix C). Our main results remain robust: higher SITG continues to significantly associate with less model risk. Additionally, we replicate Table 4 without controls (Table C.4, in Appendix C). Again our results remain robust. Higher SITG continues to significantly associate with less model risk. The relationship with other capital remains broadly insignificant.

9. Conclusion

The incentives for CCPs to manage model risk is critical for financial stability. CCPs have become systemic over the last decade. Yet, CCPs can and do fail, if they mismanage model risk—and the failure of large CCPs could shake the global financial system. However, regulators only provide broad guidance and essentially rely on CCPs to manage model risk. Therefore, it is critical that CCPs have the right incentives to manage model risk well.

We investigate how well CCP incentives are aligned to manage model risk, i.e., to right-size portfolio-specific initial margin. To the best of our knowledge, we are the first to investigate this question empirically. We examine portfolio-specific initial margin setting, while the literature has—so far—investigated only aggregate IM setting.

Our hypotheses on how these incentives might work build on the literature that shows that the more a CCP stands to lose from mismanaging model risk, the more carefully it sets IM (Carter and Garner 2015; Saguato 2017; Huang 2019). First, and most important, higher SITG is expected to associate with lower model risk. Second, other capital, as it is not affected by credit losses, is not expected to associate with model risk. We find robust evidence that supports our first hypothesis.

The results are policy relevant, particularly for central banks and financial regulators concerned about financial stability. Unlike for banks' minimum capital requirement, there is no broadly accepted minimum requirement for CCPs' SITG. Our results suggest that such SITG requirements might strengthen CCP incentives to reduce model risk—and thereby strengthen financial stability. Importantly, this effect seems to work only through SITG and not other capital. Therefore, our findings serve as a useful starting point for thinking about SITG requirements.

One important caveat is that our results should not be read as a policy prescription. We do not undertake a detailed cost-benefit analysis of SITG capital regulation. The results suggest that higher skin in the game is associated with lower model risk. However, this is only one part of the relevant policy trade-off. On the other side, there might be other consequences that need to be evaluated carefully. For instance, higher SITG might lead to higher IM, which could increase the cost of clearing derivative trades centrally. The resulting higher trading costs could prevent hedging trades for real economic actors—thereby increasing financial risks in the real economy. Future research should explore such trade-offs further before arriving at firm policy recommendations.

Appendix A. Variable Summary

Table A.1. Variables Used in Regressions

Variable	**Definition**
SITG	Dollar amount of CCP skin in the game
IM	Dollar amount of initial margin
Asset	Dollar amount of total asset
Number of Breaches	The number of margin breaches which occurs when the required VM payment exceeds the required IM
Achieved Coverage	The percentage of the trades that do not have margin breaches in the total number of trades
Diff. Coverage	The difference between the achieved coverage and the target coverage set by CCPs ex ante
Avg. Breach	The average size of margin breaches
Max. Breach	The maximum size of margin breaches

Note: This table summarizes the variables used in regressions in the paper.

Appendix B. Quarterly Increment in the Number of Margin Breaches

In the quantitative disclosure data, CCPs report the number of margin breaches for the past 12 months. Let X_t denote the number of breaches reported at time t, where $t = 0, 1, 2, \hat{a}e|T$. Let Y_t denote the quarterly increment at time t where $t = -3, -2, \hat{a}e|T$. Thus,

$$X_0 = Y_{-3} + Y_{-2} + Y_{-1} + Y_0.$$

To back out the quarterly increment for all periods, we assume $Y_{-3} = Y_{-2} = Y_{-1} = Y_0$, which equals $X_0/4$. With that, we have

$$Y_t = X_t - X_{t-1} + Y_{t-4}. \tag{B.1}$$

Appendix C. Appendix Robustness Tables

Table C.1. Regression Results with SITG and Other Equity

	Number of Breaches	**Achieved Coverage**	**Diff. Coverage**	**Avg. Breach**	**Max. Breach**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
SITG	–0.24**	0.07*	0.09**	–0.04*	–1.51*
	(–2.07)	(1.89)	(2.29)	(–1.81)	(–1.89)
Other Capital	1.19	–2.37***	–2.58***	–0.16	–1.87
	(0.66)	(–3.99)	(–5.51)	(–1.15)	(–1.47)
IM	–0.15	–0.05	0.00	–0.04	–1.92**
	(–0.66)	(–1.12)	(0.04)	(–0.66)	(–2.54)
Asset	–0.01	0.01*	0.01*	0.00	–0.06
	(–0.22)	(1.77)	(1.73)	(0.38)	(–1.06)
Constant	43.89***	9,993.63***	144.55***	4.04***	110.88***
	(6.33)	(4,836.83)	(61.52)	(3.64)	(3.33)
R-squared	0.008	0.005	0.000	0.012	0.095
N	557	557	557	168	168

Note: t-statistics are in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table C.2. Regression Results with SITG and Profit

	Number of Breaches	Achieved Coverage	Diff. Coverage	Avg. Breach	Max. Breach
	(1)	(2)	(3)	(4)	(5)
SITG	–0.24**	0.07*	0.10**	–0.04*	–1.51*
	(–2.08)	(1.96)	(2.35)	(–1.81)	(–1.89)
Profit	0.00	–0.01	–0.00	–0.00	–0.00
	(0.89)	(–1.53)	(–1.45)	(–0.71)	(–0.46)
IM	–0.16	–0.04	0.01	–0.04	–1.91**
	(–0.68)	(–1.07)	(0.16)	(–0.65)	(–2.53)
Asset	–0.01	0.01*	0.01*	0.00	–0.06
	(–0.20)	(1.76)	(1.69)	(0.36)	(–1.08)
Constant	45.60***	9,990.61***	141.21***	3.82***	108.30***
	(8.27)	(6,099.26)	(65.07)	(3.68)	(3.34)
R-squared	0.008	0.010	0.000	0.012	0.095
N	557	557	557	168	168

Note: t-statistics are in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table C.3. Regression Results with SITG (without controls)

	Number of Breaches	Achieved Coverage	Diff. Coverage	Avg. Breach	Max. Breach
	(1)	(2)	(3)	(4)	(5)
SITG	–0.21**	0.13**	0.15***	–0.04**	–1.12**
	(–2.17)	(2.34)	(2.67)	(–2.20)	(–2.24)
Constant	41.59***	9,988.44***	135.54***	3.28***	68.77***
	(11.08)	(4,526.88)	(61.15)	(5.22)	(3.65)
R-squared	0.006	0.010	0.000	0.010	0.045
N	603	603	603	186	186

Note: t-statistics are in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table C.4. Regression Results with SITG, Other Equity, and Profit (without controls)

	Number of Breaches	Achieved Coverage	Diff. Coverage	Avg. Breach	Max. Breach
	(1)	(2)	(3)	(4)	(5)
SITG	–0.21**	0.13**	0.15***	–0.04**	–1.12**
	(–2.16)	(2.39)	(2.72)	(–2.19)	(–2.23)
Other Capital	1.32	–0.82	–1.32**	–0.12	–1.28
	(0.65)	(–1.59)	(–2.63)	(–0.93)	(–1.27)
Profit	–0.00	–0.00	–0.00	–0.00	–0.00
	(–0.05)	(–1.50)	(–1.33)	(–0.19)	(–0.18)
Constant	39.78***	9,990.97***	137.81***	3.45***	70.52***
	(7.60)	(3,738.72)	(54.60)	(5.01)	(3.63)
R-squared	0.006	0.016	0.000	0.010	0.045
N	603	603	603	186	186

Note: t-statistics are in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

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The Usability of Bank Capital Buffers and Credit Supply Shocks at SMEs during the Pandemic*

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Were banks reluctant to use Basel III regulatory capital buffers to support lending to creditworthy SMEs during the COVID-19 pandemic? Confidential U.S. loan-level data show that banks starting the pandemic with "low capital headroom" above the Basel III regulatory buffers (i) reduced SME loan commitments by 10 percent more and (ii) were 11 percent more likely to result in borrower exits, controlling for a host of demand factors. We find credit effects across a variety of industries (comprising up to 21 percent of aggregate SME credit) as well as suggestive evidence of real effects on local employment growth during the pandemic (2 percent slower annually). This study is the first to test the *usability* of Basel III regulatory buffers *in a downturn* and contribute a bank capital-based transmission channel to the SME-pandemic literature.

JEL Codes: G20, G21, G28, D22.

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1. Introduction

> "Since the onset of the pandemic, however, questions have arisen over banks' ability and willingness to use the regulatory buffers available to them ... in a period of stress, banks might react with many of the same procyclical behaviors that we've seen in the past, such as reigning back new business activity."
>
> — S&P Global, June 11, 2020[1]

Regulatory reforms implemented after the 2008 global financial crisis (GFC) played a central role in rebuilding banking system capital to the highest level in decades (nearly double that of 2008). Despite the high level of banking system capital and significant government support measures, business lending to small and medium-sized enterprises (SMEs) was strained during the first few quarters of the COVID-19 pandemic. While much of the decline in business lending is attributable to loan demand and credit quality concerns, a key question remains as to whether banks used their large capital cushions built post-GFC to support lending to creditworthy SMEs during the pandemic. Our paper investigates a novel supply-side transmission channel related to the "usability of regulatory capital buffers." Specifically, we explore whether banks that entered the pandemic with capital ratios close to their regulatory capital buffers constrained lending to creditworthy SMEs. Introduced as part of the Basel III capital reforms, regulatory capital buffers are costly regions of "rainy day" equity capital that sit on top of minimum capital requirements and are designed by regulation to act as a buffer to absorb losses and support lending in a downturn.[2] In

[1]In addition, Andrea Enria, chair of the European Central Bank's Single Supervisory Mechanism, stated "There has been a concern that the buffers were not being used and there was a reluctance to use them" (Arnold 2021).

[2]As part of the Basel III capital reforms, the Basel Committee on Banking Supervision (BCBS) introduced a series of measures to promote the buildup of regulatory capital buffers (i.e., the capital conservation buffer, the countercyclical capital buffer, and the capital surcharge for global systemically important banks) in good times that can be drawn upon in periods of stress to support new lending activity. See BCBS (2009). In the U.S. implementation, the Federal Reserve introduced the stress capital buffer as a replacement for the capital conservation buffer. Institutional details on the implementation of regulatory capital buffers in the United States are described in Section 3.

contrast to minimum capital requirements, which are "hard" mandates that activate resolution procedures when breached, regulatory capital buffers represent a "soft" mandate that limits the bank's ability to pay dividends and bonuses until its capital stock is rebuilt. These penalties are intended to act as a warning signal that disincentivizes any unnecessary use of buffers in normal times and allows banks time to recover from unforeseen shocks.

This brings to light an important policy question. To incentivize macroprudential behavior from intermediaries, the optimal design of regulatory capital buffers must ensure that the usage of buffers is *costly enough* that banks do not unnecessarily use them unnecessarily in good times, and *yet not so costly* that they choose not to use them during downturns. In other words, do banks actually view regulatory capital buffers as a capital *cushion* (above minimum requirements), as intended by Basel III? If banks instead find it optimal during downturns to deleverage and maintain an additional cushion above this regulatory capital buffer, then the introduction of regulatory capital buffers into the capital regime becomes economically similar to raising the de facto minimum capital requirements. In this way, it becomes a question of whether banks perceive the "soft" mandate as "harder" than anticipated. We see the pandemic as a downturn that forms the first opportunity in the United States since the introduction of Basel III capital reforms to test this macroprudential question of whether regulatory capital buffers are "usable" in bad times.

At the onset of the pandemic, the Federal Reserve publicly encouraged banks to use these buffers to support the economy during the downturn.[3] However, the prospect of large pandemic-related losses during 2020 appears to have caused banks to reduce the likelihood of dipping into their regulatory buffers in an attempt to avoid incurring associated costs, despite elevated capital levels.[4] Our results are consistent with the notion that banks found these buffers

[3]See https://www.federalreserve.gov/newsevents/pressreleases/monetary20200315b.htm for the official press release.

[4]This regulatory issue expands beyond the case of the United States. In response to the concern that buffers were not be used, the European Central Bank even went as far as to provide pandemic capital relief by temporarily eliminating a significant portion of regulatory capital buffers.

too costly to use.[5,6] The proximity of a bank's capital ratio to its regulatory buffer threshold prior to the pandemic can be seen as a bank-specific measure of how binding the costs of the regulatory buffers were. For ease of exposition, we refer to banks that started the pandemic with a capital ratio relatively close to the regulatory buffer threshold as "low capital headroom" banks. We posit that banks starting the pandemic with low capital headroom were less willing to fully absorb pandemic losses without curbing lending to creditworthy borrowers. This response helps preserve capital headroom and avoids any supervisory costs associated with dipping into regulatory capital buffers. In Section 6, our event-study analysis suggests that the costs of using these buffers can be relatively large during downturns, implying regulatory capital buffers were likely too costly to use during the COVID-19 pandemic.

Figure 1 shows an outsized decline in the number of reported private SME exposures from low capital headroom banks during the pandemic whereas the number for high capital headroom banks remained relatively stable.[7] While some lending relationships may have ended due to pandemic-related demand-side factors, the relative difference between the two lines (high and low capital headroom banks) suggests that a sizable number of SMEs may have experienced credit supply shocks during the pandemic due to the usability of regulatory capital buffers.[8] We highlight a few facts to better understand the characteristics of firms that lost access to credit with low capital headroom banks during the pandemic period (Figure 1, red line). First, the affected firms were relatively small and bank dependent—the median borrower had assets of about \$8 million, and the largest firm had assets of about \$35 million. Nearly all firms in

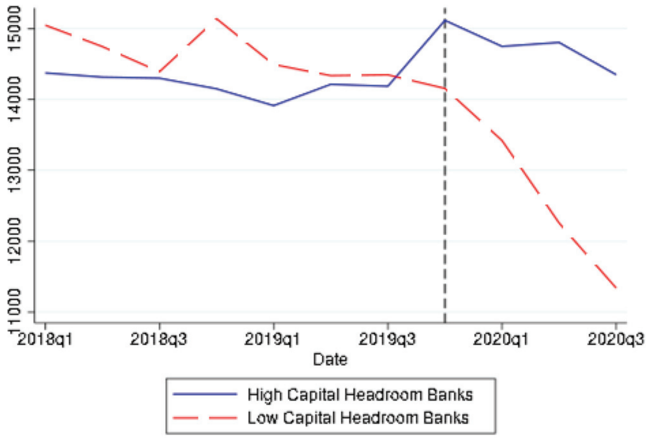
[5]Specifically, there are at least three reasons that the usage of regulatory buffers might prove costly for banks. First, associated dividend restrictions may lead to market stigma concerns for bank shareholders. Second, associated bonus restrictions for executive compensation may prove too costly for bank managers. Third, dipping into regulatory buffers may lead to downgrade risk from credit rating agencies, which can lead to an increase in bank funding costs.

[6]Unlike banks in several other countries, U.S. banks did not dip into their regulatory buffers during the pandemic.

[7]As described in Section 4, we define a firm to be an SME if the firm size is less than the median firm size in the sample as of 2019:Q4.

[8]This is covered more formally in our borrower exit specifications.

Figure 1. Bank Capital Headroom and the Number of SMEs



Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and global systemically important bank (G-SIB) surcharges to calculate the capital headroom.
Note: This plot shows the number of SMEs in the FR Y-14Q by lender type (low versus high capital headroom banks) as of each date. The relative difference between the two lines provides suggestive evidence that many SMEs (borrowing from low capital headroom lenders) exited the FR Y-14Q during the pandemic due to credit supply effects related to the usability of regulatory capital buffers. Low capital headroom banks are lenders that start the pandemic with a capital ratio relatively close to the regulatory buffer threshold.

our sample had lending relationships with only one bank. This suggests these firms may have found it costly to substitute toward other sources of financing. Second, the small firms were highly profitable, demonstrating an average return on assets of about 15 percent pre-pandemic. Third, borrower leverage, measured as debt-to-assets, averaged about 30 percent, suggesting this set of firms were prudently managed and not highly leveraged. Lastly, these borrowers were spread across all 50 states and a diverse set of industries. On average, low capital headroom banks lent to less leveraged and more profitable firms, as compared to high capital headroom banks. Taken together, these facts suggest SMEs that banked with low capital headroom banks were creditworthy and may have lost access to credit for reasons other than demand-side considerations.

To examine the finding suggested by Figure 1 more formally, we utilize a novel set of confidential, supervisory loan-level data (FR Y-14Q) between the largest U.S. banks and their corporate borrowers.[9] The granular data provide us with a unique advantage to observe the lending outcomes at an important yet understudied segment of the economy, namely, private SMEs. Although identification of a credit supply effect would ideally compare changes in lending across two banks lending to the same firm (Khwaja and Mian 2008), nearly all private SMEs have a single lender in our data. To overcome the identification challenge for single-bank SMEs, we proceed with two approaches.[10] Firstly, we follow the Degryse et. al (2019) approach and compare the lending of low versus high capital headroom banks to *groups of similar borrower firms*. Specifically, these borrowers are grouped by industry*firmsize*location*time fixed effects.[11] In this way, our analysis shows that the relative closeness of a bank's capital ratio to the costly regulatory buffer region leads to significant changes in credit growth to a variety of firm groups, after controlling for time-varying demand shocks that are common to all firms within each group. We also present evidence of parallel trends for pre-pandemic credit growth across treatment and control groups. Secondly, we provide additional robustness for the purpose of identifying credit supply shocks, by showing evidence that low capital headroom banks contract credit to firms *whose*

[9]Given the minimum loan reporting threshold of USD 1 million, these data exclude small business loans (according to the thresholds defined in Call Reports). Y-14 data also exclude Paycheck Protection Program loan balances.

[10]Another point to note is that while the ex ante size of excess capital headroom may be endogenous with respect to future lending opportunities, these headroom sizes did not incorporate the arrival of the pandemic recession, as it was an unanticipated event. Thus, the size of capital headroom is orthogonal with respect to changes in risk or lending opportunities associated with the unexpected arrival of the COVID-19 pandemic recession.

[11]In both the intensive margin (panel) and borrower exit (cross-sectional) specifications to follow, these firm groups will be implemented via fixed effects. In the panel data specifications, the fixed effects will include an interaction with date, i.e., firmsize*industry*county*date. Please note that instead of the firm*time fixed effects (which would absorb single-bank firms) in the Khwaja and Mian approach, we use firm group*time fixed effects. Here firm groups are defined by size-industry-county combinations. In other words, to include single-bank firms in the estimation, we rely on grouping firms by size*industry*county buckets, as proposed by Degryse et al. (2019).

pre-pandemic credit lines contractually matured at the peak of the pandemic (as compared to similar firms whose credit lines were contractually locked in). This exercise provides additional robustness for the purpose of identifying credit supply shocks, as the selection rule for these treatment firms (firms with maturing credit lines) comes from a predetermined variable (i.e., the maturity of a pre-pandemic contract), which was determined several years prior to the unanticipated arrival of the pandemic. This suggests the results are not driven by changes in loan demand during the pandemic, but rather by a supply-side change in bank credit policies. Specifically, this result is consistent with the notion that banks needing to shed loan exposures (e.g., to avoid using their regulatory capital buffers) find it less costly to cut lending to this specific group of firms from a legal and contractual standpoint. In this way, the lender avoids any costs associated with violating contract terms of a pre-existing commitment. In this way, banks can shed exposures in a cost-efficient manner by choosing not to renew loan commitments to firms whose credit lines are up for renegotiation.[12]

Additionally, we utilize the granularity of the data to explore a second question: did low capital headroom banks curtail lending to certain *types* of firms more than others during the pandemic? First, low capital headroom banks disproportionately curtailed lending to private SMEs while leaving their valuable relationships with large public ("core") clients untouched. Second, low capital headroom banks curbed credit to firms whose lending relationship was relatively young (less than the median relationship age of six years). This is consistent with the literature on relationship lending (Bharath et al. 2011), which attributes a larger termination cost associated with older relationships.

With parallel trends in pre-pandemic commitment growth between low capital headroom banks and high capital headroom banks, we find that SMEs borrowing from low capital headroom banks were up to 11 percent more likely to exit during the pandemic.

[12] Any interpretation of this result as being reflective of loan demand is unlikely, as this would require proposing a story for why firms with pre-existing credit lines that happen to mature during the *unanticipated* arrival of the pandemic would have lower loan demand than firms whose credit lines were contractually locked in during the pandemic.

Furthermore, low capital headroom banks reduced loan commitment growth to SMEs by an average of 10 percentage points more annually during the pandemic than high capital headroom banks did. In aggregate, these credit effects comprise up to 21 percent in terms of aggregate SME commitments.[13] We also present some evidence that reductions in access to credit are associated with real effects at the industry-county level. Since our data do not contain information on firm-level employment, we show that industry-counties that borrowed from low capital headroom banks demonstrate 2 percent slower annualized employment growth during the pandemic as compared to industry-counties without such liabilities.

The evidence presented in our paper suggests regulatory capital buffers act as a "double-edged" policy sword, where the costliness of regulatory capital buffers that incentivized banks to raise their common equity tier 1 (CET1) ratios to historically high levels *during normal times* likely also made buffers *difficult to use during the downturn.* In a general sense, our findings uncover a novel transmission channel emanating from constraints related to bank capital that led to credit supply shocks during the pandemic, which potentially delayed the economic recovery for private SMEs. Rather than seeing the regulatory capital buffers as a cushion to be drawn upon during a downturn, as intended by Basel III, banks seem to have treated regulatory buffers as de facto minimum requirements. Proposing policy recommendations to improve the usability of capital buffers requires identifying the specific costs associated with their usage that are most binding for banks. As explored in Section 6, potential policy recommendations include improving the transparency of the buffer requirement to reduce market stigma—for example, reassuring market participants and credit-rating agencies that bank decisions to dip into their buffers do not necessarily signal weakness—or providing temporarily relief from the buffer constraint in downturns. Beyond this, if some form of buffer relief is granted, banks may still not find it incentive compatible to use buffers in a

[13] In the appendix, we explore whether borrowers with low capital headroom banks were more likely to source funds from the Paycheck Protection Program (PPP). Our results suggest there is no statistical difference in the likelihood that a low capital headroom bank (versus a high capital headroom bank) substitutes toward PPP lending. This suggests the probability of these credit effects potentially translating into real effects is non-trivial.

downturn if clear forward guidance is not provided about the precise time frame of the relief (Arnold 2021, International Monetary Fund 2021).

Section 2 summarizes related literature, Section 3 provides background on the capital buffer regime under Basel III, Section 4 describes our empirical specifications, Section 5 discusses our main results, Section 6 presents findings from robustness exercises, Section 7 highlights a few policy considerations, and Section 8 concludes.

2. Literature Review and Contribution

New to the COVID-19 literature, our paper uncovers the presence of a *transmission channel emanating from regulatory capital buffer constraints* that significantly impacted SMEs during the pandemic. Complementing studies that document the performance of SMEs during the pandemic, our paper establishes a supply-side transmission channel that likely contributed to a delay in economic recovery after the pandemic. Thus, our study contributes a new bank capital angle to an expanding literature that studies the various effects of the COVID-19 pandemic shock on the condition of private SMEs. For example, Bloom, Fletcher, and Yeh (2021) use survey data on an opt-in panel of around 2,500 U.S. small businesses to assess the impact of COVID-19 and find a significant negative sales impact that peaked with an average loss of 29 percent in sales. Of these, almost a quarter reported losses of more than 50 percent. In addition, they find these impacts to be persistent, as firms reporting the largest sales drops in mid-2020 were still forecasting large sales losses a year later in mid-2021. Gourinchas et al. (2020) estimate the impact of the COVID-19 crisis on business failures among SMEs in 17 countries using a large representative firm-level database. They estimate a large increase in the failure rate of SMEs under COVID-19 of nearly 9 percentage points, absent government support. Alekseev et al. (2020) use survey data collected via Facebook and find that about a quarter of small businesses had access to financing from financial institutions, and most small businesses were reliant on personal savings and informal sources of financing during the pandemic. Kapan and Minoiu (2021) find that despite the unexpected surge in credit line drawdowns at the onset of the COVID-19 pandemic, banks with significant exposures to credit lines tightened their lending standards and cut their commercial and industrial (C&I) loan supply to small businesses. Chodorow-Reich et al. (2020) document that, unlike large firms, SMEs take loans of shorter maturity, have less active maturity management, post more collateral, pay higher spreads, and have higher utilization rates. These facts, in their view, explain why during the pandemic SMEs did not draw down their credit lines as much as large firms did. Strahan and Li (2021) analyze the bank supply of credit under the emergency Paycheck Protection Program and conclude that PPP loans reflect a benefit of bank relationships, as they facilitate firms' access to government-subsidized lending. Our results are consistent and complementary to the findings in these papers, and cover a broader class of firms (those with young lending relationships as well as credit lines maturing at the peak of the pandemic). In addition, our paper contributes a novel bank capital-based *transmission channel* that affected firms during the pandemic due to the procyclical lending response to the usability of capital buffers.

In relation to the literature studying the credit impacts of *"hard-mandate"* capital requirements (Basel Committee on Banking Supervision 2009; Kashyap, Stein, and Hanson 2010; Hanson, Kashyap, and Stein 2011; Acharya, Engle, and Richardson 2012; Admati et al. 2014; Aiyar et al. 2014; Baker and Wurgler 2015; Greenwood et al. 2017), relatively little is known about the effects of new Basel III "soft-mandate" policy tools, such as regulatory capital buffers, *particularly during downturns like the pandemic.*[14] This literature can be categorized into two groups. The first set of papers present evidence on pre-Basel III changes in capital regulation and unequivocally find that higher regulatory requirements reduce bank lending. Jiménez et al. (2017) study bank lending responses to dynamic provisioning experiments in Spain and find that countercyclical regulatory capital buffers help to smooth credit cycles. Using European banking data, Gropp et al. (2019) provide evidence for

[14] Minimum requirements are "hard" mandates that send a bank into resolution when breached. Regulatory capital buffers, on the other hand, are "soft" requirements that impose penalties if breached, while allowing banks time to recover. For example, if the buffer is breached, the bank's ability to pay dividends and bonuses is restricted until its capital stock is rebuilt.

a similar lending response to the 2011 European Banking Authority capital exercise, showing that large European banks (required to maintain a higher capital ratio in the 2011 capital exercise) responded by reducing total asset size, while keeping equity capital and asset risk constant. Behn, Haselmann, and Wachtel (2016) and Fraisse, Lé, and Thesmar (2020) use German and French loan-level data, respectively, to show that banks are more likely to cut lending when capital charges on loans, under Basel II rules, increase. Meanwhile, the second set of papers based on U.S. loan-level data explore the impact of Basel III regulatory capital buffers on lending outcomes *during normal times*. Specifically, Berrospide and Edge (2019) find that the introduction of regulatory capital buffers emanating from stress-test disclosures led to a lower growth in C&I loan commitments, while Favara, Ivanov, and Rezende (2021) find that time variation in global systemically important bank (G-SIB) surcharge regulatory buffers result in significant declines in C&I loan commitments by G-SIBs. As both of these papers concentrate on normal periods, they both contribute the important finding that soft-mandate Basel III regulatory capital buffers did in fact play a key role in getting bank system capital to the historically high levels prior to the arrival of the pandemic. Our paper can be seen as a combination of both categories, as it is the first to empirically test whether the *Basel III* regulatory buffers were in fact usable *during a (pandemic) downturn*. We find evidence pointing to procyclical impacts of regulatory capital buffers during the pandemic downturn, particularly on private SMEs and other non-core firms for which it was relatively cheap to cut lending to. Couaillier et al. (2022) have found evidence for the lending impact of buffer usability during the pandemic in the context of European banks.[15]

Finally, our results also point to a different interpretation of the Basel III regulatory capital buffers. Rather than seeing the

[15] Additionally, several papers have explored the impact of capital buffers on related issues in Europe during the pandemic. Altavilla et al. (2023) note that during the pandemic there was an important complementarity between buffer releases and monetary policy easing. Budnik et al. (2021) focus on the measures taken by supervisors, macroprudential authorities, and national governments. Borsuk, Budnick, and Volk (2020) run a simulation that suggests that banks' use of capital buffers results in higher lending and better economic outcomes.

buffers as a cushion to be drawn upon during a downturn, as originally intended by Basel III, banks seem to be treating the regulatory buffers as higher minimum requirements. Several studies have been conducted to enumerate various possible reasons why banks may or may not find buffers expensive. Abad and Pascual (2022) use market expectations to show that banks only decide to use their buffers if the value creation from a larger loan book offsets the costs associated with a capital shortfall, which the authors find to be a rare occurrence. The April 2021 Global Financial Stability Report (GFSR) from the International Monetary Fund (IMF) addressed the usability of capital buffers and documents that, despite the vital role of capital buffers to ensure continued supply of credit to the real economy, banks remain reluctant to draw down their buffers.[16] Using a sample of 72 large global banks, representing 60 percent of the global banking system's aggregate market capitalization, the report finds that only banks accounting for 5 percent of market capitalization clear the hurdles to use their buffers. Thus, banks seem to lack the economic incentives to dip into their capital buffers, as regulation requires them to rebuild their buffers later. Low returns could make the usability of buffers a costly option if the additional value generated by the new lending does not offset the negative impact from the capital shortfall resulting from using the buffers in the first place. Schmitz et al. (2021) analyze possible stigma effects arising from distribution restrictions associated with a breach in the capital buffers for European banks during the pandemic.[17] Their analysis explores potential negative spillover effects to overall bank funding costs, and finds evidence against this channel. Kleinnijenhuis, Kodres, and Wetzer (2020) point to a lack of usable capital and propose several possible improvements in the current capital framework that could overcome such issues, such as setting clear expectations about the pathway banks should follow to rebuild their buffers post-crisis.

[16] See Chapter 1, "An Asynchronous and Divergent Recovery May Put Financial Stability at Risk," pages 22–25.

[17] On a related note, Dautovic et al. (2021) study the impact of payout restrictions during the pandemic and find that European banks that paid out less than planned tended to have higher loan growth.

3. Capital Ratios and Basel III Regulatory Capital Buffers

This section outlines some background on the CET1 capital ratio and regulatory capital buffers, as implemented in the United States via Basel III. Bank CET1 capital ratios can be split into three parts:

CET1 Capital Ratio = Minimum Requirement + Regulatory Capital Buffers + Excess Headroom.

(i) A regulatory minimum requirement to prevent undercapitalization. Following the Basel III capital rules, this is 4.5 percent for all banks and marks the ("hard" mandate) threshold below which a bank would be deemed insolvent by regulators. If a bank enters this regime, resolution procedures would be set in motion.[18]

(ii) Basel III regulatory capital buffers, such as the G-SIB surcharge, the countercyclical capital buffer (CCyB), and the stress capital buffer.[19] These are costly regions of "rainy-day"

[18] Several papers provide theoretical rationale for why banks find it optimal to maintain an equilibrium level of capital in excess of regulatory minimum requirements. Using a dynamic equilibrium model of relationship lending in which banks are unable to access the equity markets every period and the business cycle determines loans' probabilities of default, Repullo and Suarez (2013) show that banks hold endogenous capital buffers as a precaution against shocks that impair their future lending capacity. Koch, Richardson, and Van Horn (2016) compare optimal capital structure prior to the Great Depression, when no government guarantees existed, versus that of the Great Recession, and suggest that market discipline would have induced the largest U.S. banks to maintain higher capital buffers prior to the 2008 crisis. Baron (2020) further provides support for the case of strengthening countercyclical capital buffers since government guarantees can distort the incentives of banks to raise new equity and affect the dynamics of bank capital structure over the credit cycle. Nier and Zicchino (2008) provide evidence that losses lead to greater pull-back in lending for banks at a lower initial level of capital.

[19] The stress capital buffer (SCB) replaced Basel III's 2.5 percent capital conservation buffer in the United States in 2020 and integrated the Federal Reserve's non-stress regulatory capital requirement with its stress-test-based capital requirement. More specifically, the SCB requirement is calculated as the difference between the banks' starting and minimum CET1 capital ratios under the severely adverse scenario in the supervisory stress test plus four quarters of the bank's planned common stock dividends. It is floored at 2.5 percent.

capital that come with payout and bonus restrictions ("soft" mandate). Whereas the CCyB is symmetric across banks, the G-SIB surcharge and stress capital buffer vary across banks, depending on the bank's risk profile. These buffers are designed to provide added resilience to absorb bank losses in the event of a stress scenario.

(iii) Excess headroom reflects the amount of CET1 capital ratio in excess of the sum of (i) regulatory minimums plus (ii) regulatory buffers. For most large firms, this cushion is typically 3 percent or less. This excess cushion approximates the amount of capital that banks could lose without facing potential payout/bonus restrictions.

For illustrative purposes, Figure 2 depicts a hypothetical bank with a starting CET1 capital ratio of 12 percent. The bank's capital ratio is decomposed into a 4.5 percent Basel III minimum requirement, a 5.5 percent regulatory buffer representing the combination of the stress capital buffer and G-SIB surcharge, and an additional 2 percent headroom. As the bank's CET1 capital ratio declines due to the arrival of pandemic losses (downward-sloping blue line), the right panel of Figure 2 (in red) highlights an important choice the bank has to make regarding lending decisions. Specifically, the bank has two options:

(i) Shrink (e.g., by constraining credit) in order to remain above the regulatory buffer threshold. This saves the bank any costs associated with dipping into the buffer (i.e., payout restrictions, bonus restrictions, etc.).

(ii) Dip into the regulatory buffers to absorb pandemic losses and continue supporting creditworthy firms through the provision of lending.

Figure 3 presents the evolution of average CET1 headroom through the pandemic. Banks appear quick to replenish their pre-pandemic headroom levels by the third quarter of the pandemic, suggesting credit supply shocks associated with the usability of regulatory capital buffers are likely to be most prominent in the early part of the pandemic.

Figure 2. Visualizing the Bank's Decision to Avoid or Use Regulatory Buffers

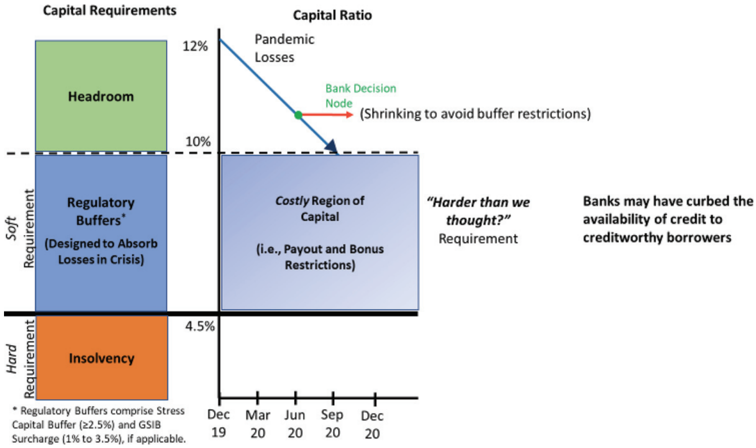
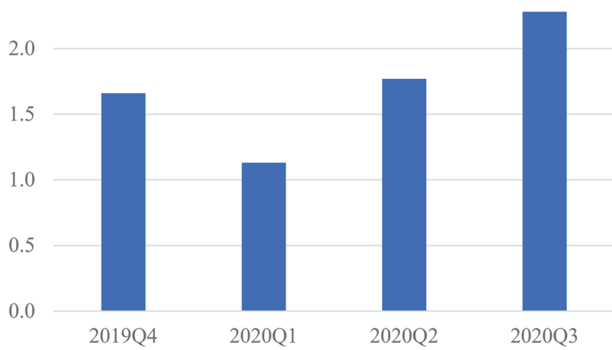


Figure 3. Evolution of CET1 Headroom



Source: FR Y-9C, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This plot shows the time-series evolution of average CET1 headroom across the 16 banks in the sample (weighted by total risk-weighted assets). Banks are quick to replenish their pre-pandemic headroom levels by the third quarter of the pandemic, suggesting credit supply shocks associated with the usability of regulatory capital buffers are likely to be most prominent in the early part of the pandemic.

4. Empirical Approach

4.1 Data Description and Summary Statistics

To perform our regression analysis, we access novel loan-level information on C&I credit lines (at the bank-firm-quarter level) sourced from the H1 Corporate Schedule of the confidential regulatory filing FR Y-14Q, and combine this with quarterly consolidated bank balance sheet level information at the bank holding company (BHC) level from the FR Y-9C regulatory filing. The FR Y-14Q Corporate Schedule is collected for very large BHCs that participate in the Comprehensive Capital Analysis and Review (CCAR) stress tests. While there are over 30 such BHCs that file, we exclude the filings of the U.S. intermediate holding companies (IHCs) of foreign banks, since the capital ratios of IHCs are internal to the organization and thus not subject to the same incentives.[20] In addition, we drop any BHCs that do not report in the FR Y-14Q during the pandemic, or those that have too little C&I loan exposure (i.e., custodian banks). Additionally, to keep the focus on lending outcomes at non-financial corporations, we exclude C&I loans to U.S. and foreign banks, other depository financial institutions, non-depository financial institutions, and loans to financial agricultural production and other loans to farmers. This leaves us with quarterly loan information for 16 domestic U.S. BHCs (413,953 bank-firm-time observations) between 2018:Q1 and 2020:Q3. The data in the FR Y-14Q Corporate Schedule includes loan information at the credit facility level for committed balances greater than or equal to \$1 million.[21] The advantage of using loan commitments is that they include both undrawn and drawn portions of credit facilities. This measure of commitments (rather than on-balance-sheet outstanding loan amounts) is immune to demand-driven swings in credit line drawdowns and repayments and is thus closer to the idea of bank credit supply decisions, compared to most other studies that use outstanding loan amounts.

[20] In addition, the excess headroom of the foreign parent of the IHC (located in the foreign home country) is unknown due to the confidentiality of a particular regulatory capital buffer implemented in Europe, known as the Pillar 2 guidance.

[21] For this reason, FR Y-14Q does not capture very small business lending (<\$1 million USD), and instead captures SMEs as well as large public firms.

The main balance sheet variable of interest that separates the set of treatment and control firms in our baseline specification is the lender's pre-pandemic distance to the regulatory buffer (as of 2019:Q4). This is equivalent to the size of the green excess capital headroom from Figure 2. Note that we use the standardized CET1 ratio in the calculation of the excess capital headroom.[22] As will be elaborated in the next section, we define a bank as being constrained by the regulatory buffer if the distance between its CET1 capital ratio and its regulatory buffer threshold is equal to or less than that of the median (2.14 percent). In other words, we posit that if a bank enters the pandemic with a relatively small headroom to absorb pandemic losses before having to dip into its regulatory buffers (and thereby incur a variety of regulatory costs), that bank may choose to curtail credit in order to avoid incurring any costs from regulatory buffer usage. We consider this a potentially undesirable outcome given that the CET1 ratio before the pandemic was historically high and yet went effectively unused.

Table 1, panel A, provides summary statistics at the bank-firm-time level for the control variables in our analysis across high capital and low capital headroom banks. C&I commitments have grown on average at an annualized rate of 4.33 percent at the bank-firm level. The median CET1 headroom (not shown) is 2.14 percent, underneath which we denote a bank as having low capital headroom. The average bank primarily funds its assets through deposit funding (65 percent), holds a sizable amount of liquid assets on its books (32 percent), and has maintained a quarterly return on assets of about 27 basis points. Panels B and C contain summary statistics for low capital headroom and high capital headroom banks. Compared to high capital headroom banks, low capital headroom banks are, on average, larger in total assets. Low capital headroom banks include primarily complex institutions with significant trading, derivatives, and investment banking activities and a large presence in syndicated loan markets. In contrast, high capital headroom banks are smaller on average, operate with a more traditional banking business model

[22]This is because the stress capital buffer applies to the standardized CET1 ratio, generally making it the more binding risk-based capital requirement, and because standardized CET1 ratios tend to be lower than advanced-approaches CET1 ratios.

Table 1. Summary Statistics

Variable	p10	Mean	p90	Std. Dev.
A. Summary Statistics for All Banks				
Annualized Growth in Commitments (%)	–24.99	4.33	22.22	64.77
CET1 Headroom (%)	1.01	2.04	2.73	0.61
Bank Log Assets	18.74	20.44	21.69	1.18
Bank Deposit Ratio (Dep/Assets) (%)	55.79	65.41	75.82	10.34
Bank Liquid Asset Ratio (Liq. Assets/Assets) (%)	22.15	31.62	39.18	7.26
Bank Provisions to RWA (%)	–0.01	0.06	0.28	0.12
Bank ROA (%)	0.12	0.27	0.37	0.11
Firm Credit Rating	6.00	7.06	8.00	1.13
Firm Leverage (Debt/Assets) (decimal)	0.00	0.33	0.71	0.27
Firm Log Assets	15.31	18.43	22.57	2.75
Firm ROA (decimal), Annual	–0.02	0.09	0.24	0.17
Firm Sales Ratio (Net Sales/Assets) (decimal), Annual	0.28	2.26	4.48	2.01
B. Summary Statistics for Low Capital Headroom Banks				
Annualized Growth in Commitments (%)	–29.91	4.91	31.19	69.58
CET1 Headroom (%)	1.01	1.65	2.14	0.50
Bank Log Assets	20.12	21.34	21.73	0.52
Bank Deposit Ratio (Dep/Assets) (%)	54.56	60.76	71.67	10.60
Bank Liquid Asset Ratio (Liq. Assets/Assets) (%)	33.10	36.80	41.54	3.74
Bank Provisions to RWA (%)	–0.01	0.06	0.28	0.11
Bank ROA (%)	0.11	0.25	0.35	0.11
Firm Credit Rating	6.00	7.05	8.00	1.14

(*continued*)

Table 1. (Continued)

Variable	p10	Mean	p90	Std. Dev.
Firm Leverage (Debt/Assets) (decimal)	0.00	0.31	0.66	0.25
Firm Log Assets	15.37	18.83	22.98	2.86
Firm ROA (decimal), Annual	–0.02	0.09	0.24	0.17
Firm Sales Ratio (Net Sales/Assets) (decimal), Annual	0.26	2.16	4.40	2.01
C. Summary Statistics for High Capital Headroom Banks				
Annualized Growth in Commitments (%)	–20.03	3.51	11.06	57.28
CET1 Headroom (%)	2.44	2.59	2.75	0.13
Bank Log Assets	18.59	19.18	19.91	0.52
Bank Deposit Ratio (Dep/Assets) (%)	67.02	71.99	76.86	5.01
Bank Liquid Asset Ratio (Liq. Assets/Assets) (%)	18.44	24.29	28.70	3.98
Bank Provisions to RWA (%)	–0.02	0.06	0.28	0.13
Bank ROA (%)	0.13	0.29	0.42	0.11
Firm Credit Rating	6.00	7.07	8.00	1.11
Firm Leverage (Debt/Assets) (decimal)	0.00	0.36	0.79	0.28
Firm Log Assets	15.25	17.88	21.69	2.48
Firm ROA (decimal), Annual	–0.03	0.09	0.24	0.17
Firm Sales Ratio (Net Sales/Assets) (decimal), Annual	0.33	2.40	4.58	2.00

Source: FR Y-9C, FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom. Note that the definition of Firm Credit Rating is 1 for NR, 2 for D, 3 for C, 4 for CC, 5 for CCC, 6 for B, 7 for BB, 8 for BBB, 9 for A, 10 for AA, and 11 for AAA.
Note: This table provides summary statistics for key variables in the FR Y-14Q data. The table reports the 10th percentile, mean, 90th percentile, and standard deviation for both BHC variables and firm variables. There are 413,953 bank-firm-time observations, which are spread across 16 lenders and 11 quarters. Low capital headroom banks have 242,498 observations.

(e.g., more reliant on deposits to fund their asset portfolios) and maintain an important regional presence. These banks are similar to high capital headroom banks in terms of loan loss provisions, and larger in terms of asset liquidity. Credit quality, as measured by banks' internal ratings assigned to borrowers, is similar across both bank types, suggesting that neither bank group started the pandemic with significantly riskier lending portfolios. On average, low capital headroom banks lend to less leveraged and equally profitable firms.

One appeal of the FR Y-14Q data set is that it includes a wide range of firms; that is, small and large firms, as well as publicly traded and private firms. Our use of the FR Y-14Q C&I loan-level data is quite novel, as this is the closest data set that the United States has to credit registry data.[23]

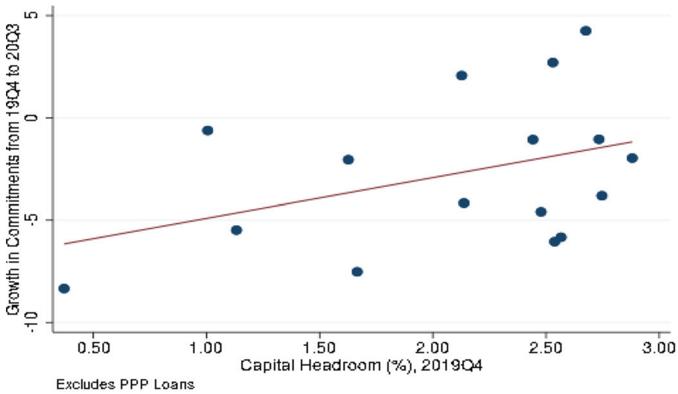
Figure 4 plots the relationship between the size of the capital headroom, measured as of 2019:Q4, versus the subsequent growth in C&I loan commitments during the pandemic period. The figure shows that commitment growth during the pandemic was weaker among banks that had low capital headroom ex ante—that is, those that entered the pandemic with CET1 capital ratios closer to the regulatory buffer.[24]

Next, we plot time trends by comparing C&I commitment growth rates across low versus high capital headroom banks. Suggestive of parallel trends, Figure 5 shows the average commitment growth rates before and after the pandemic for firms that borrow from low capital headroom lenders (red) versus high capital headroom lenders (blue). As shown in the figure, overall C&I commitment growth rates declined significantly after the pandemic, that is, from 2019:Q4 to 2020:Q3. The contraction was more severe for low capital headroom banks than for high capital headroom banks.

[23]While it is true that many studies using bank-borrower data focus on single countries, there are also studies focusing on several euro-area countries, such as Altavilla et al. (2020) and Altavilla et al. (2021).

[24]Please refer to the appendix for further analysis showing that this relation cannot be explained by plotting the pre-pandemic level of the CET1 ratio versus the pandemic commitment growth. Counter to intuition, excess capital cushions are not positively correlated with CET1 ratios.

Figure 4. Capital Headroom and Commitment Growth in the Cross-Section of Banks



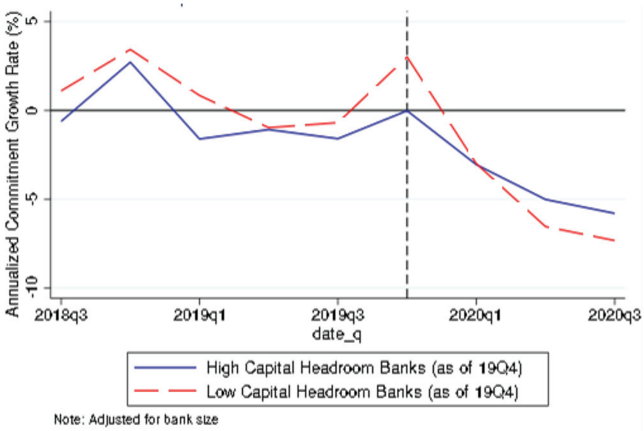
Source: FR Y-9C, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This plot explores credit effects in the cross-section of banks and shows a positive relationship between a bank's capital headroom ex ante to the pandemic (2019:Q4), and its cumulative percentage growth in loan commitments during the pandemic (from 2019:Q4 to 2020:Q3). Low capital headroom banks are lenders that start the pandemic with a capital ratio relatively close to the regulatory buffer threshold.

4.2 Regression Specifications

While using consolidated bank balance sheet data is less suitable for disentangling credit supply from credit demand, to overcome this issue, we use loan-level data on C&I credit lines. To account for all changes in lending, the credit effect analysis is broken into a cross-sectional borrower exit analysis as well as a panel data intensive margin analysis. Our cross-sectional specification for the borrower exit analysis considers the probability that a given pre-pandemic lending relationship ends anytime during the post-pandemic sample period, with all explanatory variables measured as of 2019:Q4. In this way, coefficients reflect a time-aggregated estimate of the total economic magnitude of borrower exits anytime during the pandemic.[25] Our intensive margin analysis uses bank-firm-date level spanning from

[25]For robustness, we show that a panel version of the borrower exit analysis leads to consistent results. These findings are presented in Tables B.1–B.3.

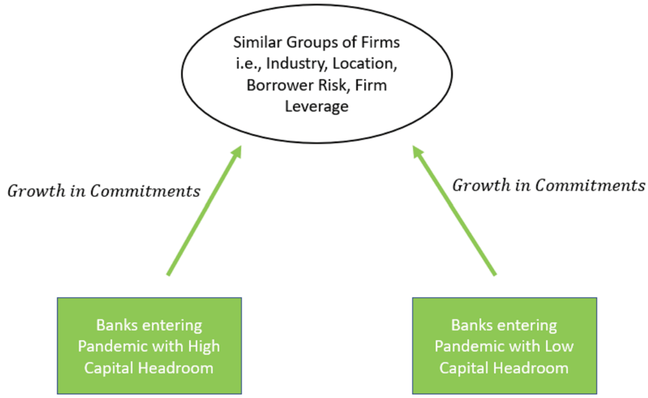
Figure 5. Bank Capital Headroom and C&I Commitment Growth through Time—Intensive Margin



Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This plot shows the time-series variation in average commitment growth across lender type. The average annualized commitment growth rate for low capital headroom banks declines more during the pandemic than that of high capital headroom banks. Low capital headroom banks are lenders that start the pandemic with a capital ratio relatively close to the regulatory buffer threshold.

2018:Q1 to 2020:Q3. Because the bulk of firms in the FR Y-14Q data borrow from a single bank, we apply the Degryse et. al (2019) approach to compare the lending of low versus high capital headroom banks to *groups of similar borrowing firms* that are likely to experience common demand shocks (see Figure 6). Specifically, our identification strategy replaces firm fixed effects with firm-type fixed effects in the cross-sectional borrower exit analysis and replaces firm*time fixed effects with firm-type*time fixed effects in the panel data intensive margin analysis. Firm type includes firms grouped by industry*county*firm size (decile). These firm-type and firm-type*time fixed effects allow us to control for demand shocks that are common to firms in the same group in the cross-sectional and panel data analyses, respectively. Moreover, for the panel data specifications, we add bank*firm fixed effects to control for any unobserved characteristics specific to a given bank-firm lending relationship. Beyond including typical firm and bank characteristics as controls,

Figure 6. Empirical Setup



Note: This diagram illustrates our empirical setup, where we compare differences in pandemic-time commitment growth across low and high capital headroom banks. As SMEs typically only have one lender, we extend the Khwaja and Mian (2008) approach and compare the lending of low versus high capital headroom banks to *groups of similar borrower firms*, based on industry*location*size*time fixed effects. Low capital headroom banks are lenders that start the pandemic with a capital ratio relatively close to the regulatory buffer threshold.

our regression specifications also control for the share of undrawn credit lines in bank assets and the share of loans granted under the Main Street Lending Program (MSLP) in bank assets.[26] As an alternative identification strategy to isolate credit supply shocks, we also perform a specification that compares lending responses of low and high capital headroom banks across firms whose pre-pandemic credit lines contractually matured at the peak of the pandemic versus firms whose credit lines did not. Here, the selection rule for assigning treatment comes from a predetermined variable (i.e., the maturity of a previous contract), which was made prior to the unexpected arrival of the pandemic and thus uncorrelated with firm-level demand shocks during the pandemic. We also explore whether the usability of capital buffers may have led to real effects. Finally, we conclude with additional robustness exercises for our credit effect results.

[26]In the appendix, we explore whether affected banks substitute to other funding sources, such as the Payment Protection Program (PPP).

4.2.1 Credit Effects (Borrower Exits)

Our first set of specifications study bank credit response with regards to borrower exits, based on Favara, Ivanov, and Rezende (2021). Figure 1 suggests this effect was significant for low capital headroom banks during the pandemic. We categorize banks as either "low capital headroom" or "high capital headroom" using a dummy variable *LowCapitalHeadroomBank*, which takes the value of 1 for banks that had CET1 capital ratios close to the regulatory buffer right before the onset of the pandemic and 0 for those that had CET1 capital ratios far from it. This threshold is based on whether this headroom is above or below the median headroom (2.14 percent) for CCAR banks as of 2019:Q4. Equation (1) below shows our cross-sectional regression specification:

$$\begin{aligned} &BorrowerExit[0/1]_{b,f,2020Q3} \\ &\quad = \beta_0 + \beta_1 LowCapitalHeadroomBank[0/1]_{b,2019Q4} \\ &\qquad + \beta_2\theta + \beta_3 LowCapitalHeadroomBank[0/1]_{b,2019Q4} * \theta \\ &\qquad + \beta_F FirmControls_{f,2019Q4} + \beta_B BankControls_{b,2019Q4} \\ &\qquad + \alpha_{FirmSize*Industry*County\ FEs} + \varepsilon_{bf}, \end{aligned} \tag{1}$$

where *BorrowerExit* is a dummy variable that equals 1 if a given firm f borrowing from bank b exits the FR Y-14Q as of 2020:Q3. The interaction coefficient β_3 captures the differential impact that low capital headroom banks have on the probability that a given borrower ends its lending relationship (exits) during the pandemic (as compared to that of a high capital headroom bank). For Tables 2, 4, and 6, θ takes on each respective element of the following set:

$$\left\{ \begin{matrix} PrivateSME[0/1]_{f,2019Q4},\ YoungRelationshipFirm[0/1]_{b,f,2019Q4}, \\ FirmCredLineMaturinginPandemic[0/1]_{b,f,2019Q4\rightarrow 2020Q2} \end{matrix} \right\},$$

where

- $PrivateSME_{f,2019Q4}$ is a dummy variable that equals 1 for all private firms f that are smaller than the median firm size in the sample as of 2019:Q4;

- $YoungRelationshipFirm_{b,f,2019Q4}$ is a dummy variable that equals 1 for all firms f that have maintained a lending relationship with their bank b for less than or equal to the median relationship age (six years), as of 2019:Q4;
- $FirmCredLineMaturinginPandemic_{b,f,2019Q4 \rightarrow 2020Q2}$ is a dummy variable that equals 1 for all firms f in 2019:Q4 whose pre-existing credit facility with bank b is set to contractually mature at the peak of the pandemic, 2020:Q2.

$BankControls_{b,2019Q4}$ include the ratio of bank MSLP loans to assets, ratio of bank MSLP state-level loans to assets, bank undrawn credit line exposure, bank size, share of deposits in assets, ratio of loan loss provisions to risk-weighted assets (RWA), share of liquid assets in total assets, and bank profitability. $Firm\ Controls_{f,2019Q4}$ include the firm probability, firm leverage as measured by the ratio of debt to total assets, firm sales ratio, and firm non-investment credit rating indicator (assigned by the bank).

According to our hypothesis, we expect a positive value for the coefficient β_3 on the interaction term, $LowCapitalHeadroomBank * \theta$. This is consistent with the hypothesis that banks entering the pandemic with relatively little capital headroom above the costly regulatory buffer region are more likely to subsequently reduce credit exposures to specific types of firms (i.e., private SMEs, those with relatively young lending relationships, and those whose pre-existing credit lines are set to mature at the peak of the pandemic) in a way that results in borrower exits.

4.2.2 Credit Effects (Intensive Margin)

Our second set of specifications study the bank lending response along the intensive margin. We categorize banks as either low capital headroom or high capital headroom using the same dummy variable *LowCapitalHeadroomBank* as in the previous subsection. Equation (2) below presents our panel data specification using the growth rate in commitments:

$$\frac{\triangle Commitments_{bft}}{Commitments_{bf,t-1}}$$

$$= \beta_0 + \beta_1 Post[0/1]_t + \beta_2 LowCapitalHeadroomBank[0/1]_{b,2019Q4}$$

$$+\beta_3\theta+\cdots+\beta_7 Post[0/1]_t * LowCapitalHeadroomBank[0/1]_{b,2019Q4}*\theta$$
$$+\beta_B BankControls_{b,t-1}+\beta_F FirmControls_{f,t-1}$$
$$+\varphi_{Bank*FirmFEs}$$
$$+\alpha_{FirmSizeDecile*Industry*County*DateFEs}+\varepsilon_{bft}, \tag{2}$$

where the "..." includes all pairwise interactions between the three interacting variables. $\frac{\triangle Commitments_{bft}}{Commitments_{bf,t-1}}$ is the growth rate in commitments from bank b to firm f at time t. We annualize this measure. $Post_t$ is a dummy variable that equals 1 starting 2020:Q1 or later. For regression Tables 3, 5, and 7, θ takes on each respective element of the following set:

$$\left\{\begin{matrix} PrivateSME[0/1]_{f,2019Q4},\ YoungRelationshipFirm[0/1]_{b,f,2019Q4}, \\ FirmCredLineMaturinginPandemic[0/1]_{b,f,2019Q4\rightarrow 2020Q2} \end{matrix}\right\},$$

where the definitions are the same as in Section 4.2.1.

$BankControls_{b,2019Q4}$ include the ratio of bank MSLP loans to assets, ratio of bank MSLP state-level loans to assets, bank undrawn credit line exposure, bank size, share of deposits in assets, ratio of loan loss provisions to RWA, share of liquid assets in total assets, and bank profitability. $Firm\ Controls_{f,2019Q4}$ include the firm probability, firm leverage as measured by the ratio of debt to total assets, firm sales ratio, and firm non-investment credit rating indicator (assigned by the bank).

For this triple difference-in-differences specifications, we expect a negative estimate for the coefficient β_7, which is associated with the triple interaction term $Post * LowCapitalHeadroomBank * \theta$. A negative coefficient would be consistent with our prediction that low capital headroom banks curb commitments disproportionately more to firms with particular characteristics: private SMEs, those with relatively young lending relationships, and those whose pre-existing credit lines are up for renegotiation at the height of the unanticipated pandemic.

4.2.3 Real Effects

Our third set of specifications explore whether the credit effects analyzed in Sections 4.2.1 and 4.2.2 translate into real effects, particularly for local employment. Data limitations prevent us from testing the impact of low capital headroom on firm-level real outcomes like corporate investment because these variables are infrequently updated for many firms in the FR Y-14Q Corporate Schedule. This is partly because the majority of firms in the data set are private and thus likely only provide updated financial information as and when requested by lenders for the purpose of obtaining bank loans and satisfying bank monitoring procedures. In addition, the FR Y-14Q does not contain data on firm-level employment. Instead, we utilize panel data on local employment growth rates at the industry-county-month level provided by the Bureau of Labor Statistics Quarterly Census of Employment and Wages (BLS QCEW) as our real outcome variable of interest. We aggregate ex ante (2019:Q4) credit exposures of low capital headroom banks to firms within each industry-county group from the FR Y-14Q data set, and merge these onto the industry-county employment growth series from the BLS QCEW.

Equation (3) below presents our panel data specification that explores whether the usability of regulatory buffers led firms located within industry-county groups (with pre-pandemic exposures to low capital headroom banks) to reduce employment growth more during the pandemic than firms located within industry-county groups (with no pre-pandemic exposures to low capital headroom banks).

$$\begin{aligned}
&\frac{\triangle Employment_{c,i,t}}{Employment_{c,i,t-1}}\\
&\quad = \beta_0 + \beta_1 Post[0/1]_t + \beta_2 LowCapHeadroomBankExposure[0/1]_{c,i,2019Q4}\\
&\qquad + \beta_3 Post[0/1]_t * LowCapHeadroomBankExposure[0/1]_{c,i,2019Q4}\\
&\qquad + \alpha_{IndustryDateFEs} + \gamma_{CountyDateFEs} + \varepsilon_{c,i,t} \qquad (3)
\end{aligned}$$

$\frac{\triangle Employment_{c,i,t}}{Employment_{c,i,t-1}}$ is the growth rate in employment at all firms in industry i located in county c at month t. We annualize this measure. *Post* is a dummy variable that equals 1 starting April 2020 or later. *LowCapHeadroomBankExposure* is a dummy variable that equals 1 if firms in county c and industry i have an aggregated non-zero exposure to low capital headroom banks prior to the pandemic (2019:Q4), and 0 if they have zero credit exposure to low capital headroom banks before the pandemic. We include industry*date and county*date fixed effects to control for demand-side shocks associated with the local county-month business cycle and industry-month trends.

According to our hypothesis, we expect a negative estimate on the β_3 coefficient for the interaction term *Post∗LowCapHeadroomBankExposure*. This would be consistent with our prediction that low capital headroom banks contract credit during the pandemic, leading to potential real effects via the reduction in employment growth at firms located in exposed industry-counties.

5. Results

Tables 2 and 3 show the regression estimates for the borrower exit and intensive margin specifications, respectively, where columns gradually add on bank controls and firm controls within each table. Columns 1 through 3 of Table 2 show the negative and statistically significant impact of *LowCapitalHeadroomBank* on the probability that a given private SME exits the FR Y-14Q (as compared to that of similar firm borrowing from a high capital headroom bank). Specifically, firms borrowing from lenders that entered the pandemic with low capital headroom were up to 11.1 percent more likely to exit during the pandemic. Along the intensive margin, Table 3 shows that low capital headroom banks curtail commitment growth rates to private SMEs by 10.3 percent more annually than high capital headroom banks during the pandemic. These magnitudes are economically meaningful, given that the average growth rate in commitments for all firms across all quarters in the FR Y-14Q is 4.33 percent, as reported in Table 1. Our results point to concerns about potential delays in the economic recovery following the peak of the pandemic, as private SMEs typically incur higher costs in substituting to other sources of financing than do large firms. The fact that low capital headroom banks did not curb credit to large borrowers is consistent with the notion that banks protect relationships with large public borrowers, as those relationships tend to be more valuable (e.g., banks can service multi-line products for large firms).

Figure 7 shows evidence of parallel trends by running a panel data version of the borrower exit specification. Specifically, we follow the methodology for parallel trends used in Kovner and Van Tassel

Table 2. Differential Credit Effect of Low vs. High Capital Headroom Banks on SMEs—Borrower Exits

	Pr(Borrower Exits during Pandemic)		
Variables	**(1)**	**(2)**	**(3)**
PrivateSME	0.000113	–0.0314***	–0.0205**
LowCapitalHeadroomBank* PrivateSME	**0.131*** **	**0.135*** **	**0.111*** **
LowCapitalHeadroomBank	–0.0969*	–0.103**	–0.0716
Firm ROA			–0.0578***
Firm Leverage			–0.0645***
Firm Sales Ratio			–0.00393**
Firm Non-investment Grade Rating			0.00467***
Bank MLSP Total Loans to Assets		0.00265***	0.00162**
Bank MLSP State-Level Loans to Assets		–0.00244***	–0.00257***
Bank Undrawn Credit Line Ratio		–0.00273***	–0.00395***
Bank Log Assets		–0.00563	–0.0200***
Bank Deposit Ratio		–0.00105***	–7.27e-05
Bank Provisions to RWA		0.0528	0.0190
Bank Liquid Asset Ratio		0.00123	0.00325***
Bank ROA		–0.0434	0.0222
Constant	0.161***	0.375***	0.524***
Observations	46,042	46,042	39,883
R-squared	0.236	0.238	0.253
FirmSize-Industry-County FE	Y	Y	Y
No. of Banks	16	16	16
No. of Firms	33,259	33,259	28,476

(*continued*)

Table 2. (Continued)

Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This table presents the regression results for the cross-sectional specification (1), focusing on private SMEs. All observations are as of 2019:Q4. The left-hand-side variable is a dummy variable that equals 1 if a given firm no longer exists in the FR Y-14Q at the end of the sample (2020:Q3). The interaction coefficient captures the differential impact that a low capital headroom bank has on the probability that a given private SME exits during the pandemic (as compared to that of a high capital headroom bank). *LowCapitalHeadroomBank* is a 0/1 variable denoting if the firm borrows from a lender whose CET1 capital ratio was relatively close to the costly regulatory capital buffer threshold (headroom $\leq$ 2.14 percent), as of 2019:Q4. *PrivateSME* is a 0/1 variable denoting if the firm is private and is smaller than the median firm size in the sample. Controls include firm- and bank-level characteristics. All specifications include fixed effects for firm-size-decile*industry*county. Standard errors are clustered by firm. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

(2022) and present the date-specific difference-in-difference coefficients (along with 90 percent confidence intervals) for the private SME subsample. These coefficients capture the relative difference in the probability that any existing SME borrower exits in the next quarter for low versus high capital headroom banks. As shown in the figure, the probability of SME borrower exits is not statistically different pre-pandemic, whereas the probability of exits for SME firms borrowing from low capital headroom banks rose post-pandemic (as compared to SME borrowers of high capital headroom banks).

Figure 8 explores firm entrants versus exits in the FR Y-14Q by lender type. While Figure 1 shows the stock of private SME exposures through time, Figure 8 shows the flow of new firm entrants and old borrower exits quarter by quarter. The top panel shows that low capital headroom banks show a significant widening during the pandemic, with higher borrower exits and lower firm entrants, whereas high capital headroom banks show no such widening.

It is important to note that the borrower exit effects occur across a variety of industries. While Figure 1 shows that low capital headroom banks exhibited larger reductions in private SME relationships during the pandemic (as compared to that of high capital headroom banks), Figure 9 illustrates the generality of this finding, as it holds for a wide variety of SME industries, including Education; Wholesale

Table 3. Differential Credit Effect of Low vs. High Capital Headroom Banks on SMEs—Intensive Margin

Variables	C&I Loan Commitment Growth Rate Perc. Pts. (Annualized)		
	(1)	**(2)**	**(3)**
*Post*LowCapital HeadroomBank*	1.189	0.142	0.245
Post*LowCapital HeadroomBank* PrivateSME	**–9.289*****	**–9.516*****	**–10.28*****
*Post*PrivateSME*	4.780**	5.052**	5.314**
Firm ROA			3.201
Firm Leverage			–10.89***
Firm Sales Ratio			0.599***
Firm Non-investment Grade Rating			–1.772**
Bank MLSP Total Loans to Assets		–0.0845	0.122
Bank MLSP State-Level Loans to Assets		0.528***	0.584***
Bank Undrawn Credit Line Ratio		–0.715**	–0.938***
Bank Log Assets		–5.996	–6.298
Bank Deposit Ratio		0.0566	0.00159
Bank Provisions to RWA		–1.985	–2.142
Bank Liquid Asset Ratio		0.501	0.625*
Bank ROA		–2.610	–3.427
Constant	4.108***	117.7	130.0
Observations	413,935	413,935	365,854
R-squared	0.294	0.294	0.307
Bank-Firm FE	Y	Y	Y
FirmSize-Industry-County-Date FE	Y	Y	Y
No. of Banks	16	16	16
No. of Firms	34,872	34,872	31,764

(*continued*)

Table 3. (Continued)

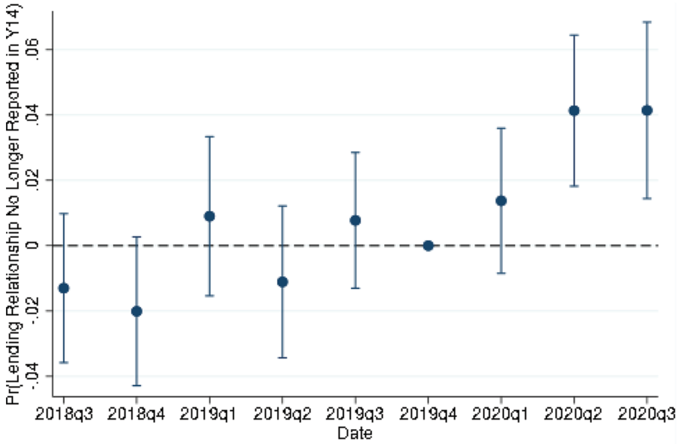
Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This table reports the regression results for panel data specification (2), focusing on private SMEs. The interaction coefficient captures the differential impact that a low capital headroom bank has on annualized commitment growth rates (along the intensive margin) to private SMEs (as compared to that of a high capital headroom bank) after the 2020:Q1 arrival of the pandemic. *Post* is a dummy variable denoting 2020:Q1 and after. *LowCapitalHeadroomBank* is a 0/1 variable denoting if the firm borrows from a lender whose CET1 capital ratio was relatively close to the regulatory capital buffer threshold (headroom $\leq$ 2.14 percent) as of 2019:Q4. *PrivateSME* is a 0/1 variable denoting if the firm is private and is smaller than the median firm size in the sample. Controls include lagged firm- and bank-level characteristics. All specifications are at the bank-firm-date level, span 2018:Q1–2020:Q3, and include bank*firm as well as firm-size-decile*industry*county*date fixed effects. Standard errors are clustered by bank-date and firm level. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

Trade; Construction; Food and Textile Manufacturing; Health Care; Information Technology; Technical Services; Retail Trade; Wood, Coal, and Plastics Manufacturing; Transportation; Administrative Services; Mining; Accommodation and Food Services; Machinery and Furniture Manufacturing; and Real Estate.[27] This shows that the issue of usability of regulatory buffers had potentially wide-reaching effects and was not limited to those industries directly affected by the COVID-19 pandemic.

Tables 4 and 5 provide borrower exit and intensive margin analysis estimates for credit supply adjustments with respect to borrowers whose lending relationships are relatively young. We define a lending relationship as relatively young if its age is below the median relationship age for all bank-firm pairs in the FR Y-14Q data (six years or less). Table 4 shows that firms having relatively young lending relationships with low capital headroom banks are 2.6 percent more likely to exit during the pandemic. Additionally, Table 5 shows that

[27]It is important to note that two industries that were highly affected by the pandemic recession were Tourism and Accommodation. Tourism (NAICS 5615) is a subsector within Administrative Services (NAICS 56), and Accommodation (NAICS 7211) is a subsector within Accommodation and Food Services (NAICS 72) in Figure 9.

Figure 7. Bank Capital Headroom and SME Exits

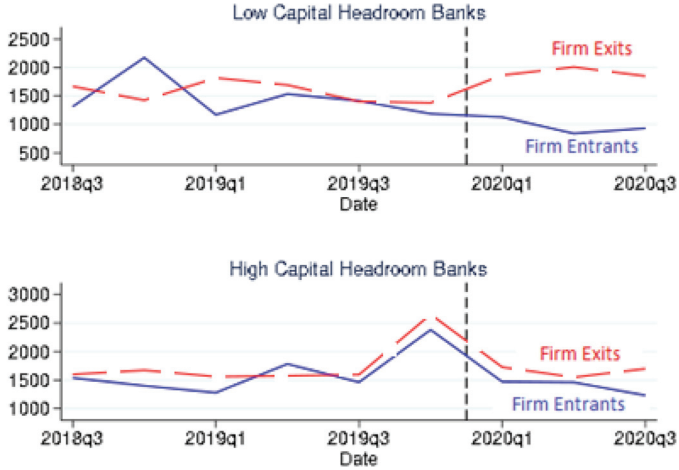


Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This chart presents the time-specific difference-in-difference coefficients $\beta_{2,\tau}$ (along with 90 percent confidence intervals) after estimating a panel data version of specification (1) for the private SME subsample, where the *Post* dummy is replaced by quarterly time dummies. These coefficients capture the relative difference in the probability that a given SME exits the FR Y-14Q in the next quarter for low versus high capital headroom lenders. Low capital headroom banks are lenders that start the pandemic with a capital ratio relatively close to the regulatory buffer threshold.

low capital headroom banks reduce annual C&I commitment growth to young relationship firms by roughly 5 percentage points more during the pandemic. This result is consistent with the idea that curtailing credit to borrowers that have a younger relationship with the bank is less costly than incurring the reputational costs associated with curtailing credit to borrowers with older relationships.

Tables 6 and 7 explore the set of firms that have credit lines originated prior to the pandemic that contractually mature in the peak of the pandemic, 2020:Q2. These are the set of firms for which it is least costly (contractually) for a bank to cut lending to, since the bank does not need to break any terms of the pre-existing contract or wait for any covenants to be violated. The bank can simply decline to renew during the contract renegotiation and allow the exposure to costlessly roll off its books. Table 6 shows that such

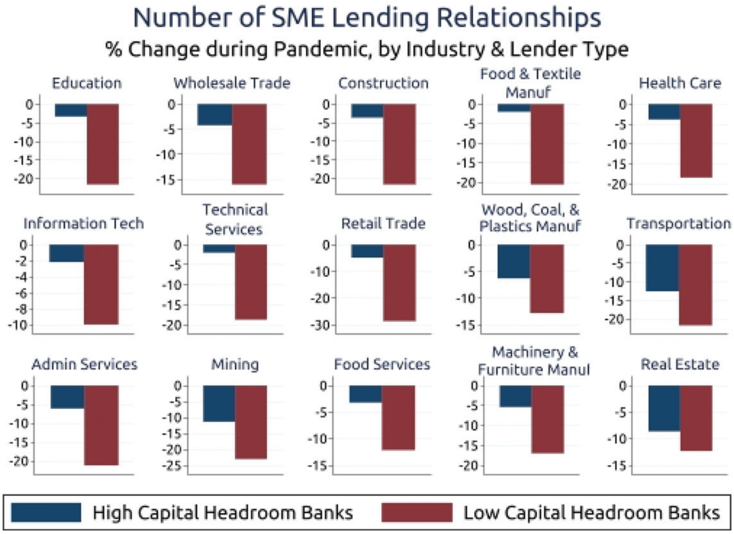
Figure 8. Firm Entry and Exit Flow



Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This plot shows the number of borrower exits and entrants (flow) in the FR Y-14Q for SMEs across low versus high capital headroom banks. Low capital headroom banks are lenders that start the pandemic with a capital ratio relatively close to the regulatory buffer threshold.

firms borrowing from low capital headroom banks are 9.6 percent more likely to exit at the peak of the pandemic, while Table 7 shows that low capital headroom banks reduced annual C&I commitment growth to these firms by 33.8 percentage points more during the pandemic (as compared to that of high capital headroom banks). Note the economic significance of this result. This magnitude is expected, as it is consistent with the idea that low headroom banks find it contractually cheaper to curtail lending disproportionately to borrowers entering a renegotiation at an unfavorable bargaining time (COVID-19). Note also that this finding provides additional robustness for the purpose of identifying credit supply shocks since the selection rule for this treatment group of firms comes from a predetermined variable (e.g., the contractual maturity of a pre-pandemic credit line contract), which was set prior to the unexpected arrival of the pandemic downturn. This finding strongly suggests the presence of credit supply effects, as it would be difficult to explain this

Figure 9. Bank Capital Headroom and SMEs by Sector



Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This chart shows the percent change in the number of SMEs during the pandemic, by low versus high capital headroom lender type and by industry. This percent change is measured by counting the total number of private SME borrowers in the FR Y-14Q as of 2019:Q4 and 2020:Q3. Low capital headroom banks are lenders that start the pandemic with a capital ratio relatively close to the regulatory buffer threshold.

result using a demand-side story. Tables 4 through 7 show that the credit effects associated with the usability of buffers expand to firms *beyond just SMEs*. Specifically, *any* firm with a young lending relationship or loans maturing at the start of the pandemic qualifies as a less costly option for low capital headroom banks to curtail lending to in order to preserve bank capital most efficiently and avoid the costs of buffer usage.

Table 8 shows the results of the employment growth regression from specification (3), providing suggestive evidence that the credit effects covered in previous tables likely led to real effects. Specifically, it is likely that SME firms borrowing from low capital headroom banks found it difficult to substitute toward other forms of finance and, thereby, may have had to adjust by reducing the growth rate of

Table 4. Differential Credit Effect of Low vs. High Capital Headroom Banks on Young Relationship Firms—Borrower Exits

Variables	Pr(Borrower Exits during Pandemic)		
	(1)	(2)	(3)
LowCapitalHeadroom Bank	0.0407***	0.00183	0.00721
LowCapitalHeadroomBank*YoungRelationshipFirm	**0.0354*** **	**0.0328*** **	**0.0257*** **
YoungRelationship Firm	0.0465***	0.0466***	0.0370***
Firm Log Assets			–0.0153***
Firm ROA			–0.0556***
Firm Leverage			–0.0677***
Firm Sales Ratio			–0.00371**
Firm Non-investment Grade Rating			–0.0431***
Bank MLSP Total Loans to Assets		0.00255***	0.00149*
Bank MLSP State-Level Loans to Assets		–0.00289***	–0.00429***
Bank Undrawn Credit Line Ratio		–0.00240***	–0.00247***
Bank Log Assets		–0.00447	–0.0219***
Bank Deposit Ratio		–6.58e-05	0.000690**
Bank Provisions to RWA		0.105	0.0795
Bank Liquid Asset Ratio		0.00283***	0.00491***
Bank ROA		–0.0158	0.0479
Constant	0.0827***	0.157*	0.691***

(*continued*)

Table 4. (Continued)

Variables	**Pr(Borrower Exits during Pandemic)**		
	(1)	**(2)**	**(3)**
Observations	46,042	46,042	39,883
R-squared	0.237	0.238	0.253
FirmSize-Industry-County FE	Y	Y	Y
No. of Banks	16	16	16
No. of Firms	33,259	33,259	28,476

Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This table presents the regression results for the cross-sectional specification (1), focusing on young relationship firms. All observations are as of 2019:Q4. The left-hand-side variable is a dummy variable that equals 1 if a given firm no longer exists in the FR Y-14Q at the end of the sample period (2020:Q3). The interaction coefficient captures the differential impact that a low capital headroom bank has on the probability that a given young relationship borrower exits during the pandemic (as compared to that of a high capital headroom bank). *LowCapitalHeadroomBank* is a 0/1 variable denoting if the firm borrows from a lender whose CET1 capital ratio was relatively close to the costly regulatory capital buffer threshold (headroom $\leq$ 2.14 percent) as of 2019:Q4. *YoungRelationshipFirm* is a 0/1 variable denoting if the firm's relationship with its lender (as of 2019:Q4) is smaller than the median relationship age in the sample (six years). Controls include firm- and bank-level characteristics. All specifications include fixed effects for firm-size-decile*industry*county. Standard errors are clustered by firm. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

employment. The difference-in-difference estimate in Table 8 shows that firms in industry-counties that entered the pandemic with non-zero credit exposures to low capital headroom banks reduce their employment by an annualized growth rate of 1.87 percent as compared to firms located in other industry-counties. Figure 10 shows evidence of parallel trends by running a modified version of the employment specification. Specifically, we present the date-specific difference-in-difference coefficients (along with 90 percent confidence intervals) for the employment growth across industry-counties, and show that the coefficients before the pandemic are not statistically different from zero. Notice that the 1.87 percentage point estimate

Table 5. Differential Credit Effect of Low vs. High Capital Headroom Banks on Young Relationship Firms—Intensive Margin

	C&I Loan Commitment Growth Rate Perc. Pts. (Annualized)		
Variables	**(1)**	**(2)**	**(3)**
*Post*LowCapital HeadroomBank*	–0.42	–1.429	–1.277
Post*LowCapital HeadroomBank* YoungRelationship Firm	**–4.400****	**–4.436****	**–5.020****
*Post*YoungRelationship Firm*	–2.594**	–2.377**	–1.633
Firm Log Assets			–1.889***
Firm ROA			3.139
Firm Leverage			–10.07***
Firm Sales Ratio			0.645***
Firm Non-investment Grade Rating			–1.574**
Bank MLSP Total Loans to Assets		–0.289	–0.105
Bank MLSP State-Level Loans to Assets		0.553***	0.637***
Bank Undrawn Credit Line Ratio		–0.618*	–0.891***
Bank Log Assets		–6.117	–5.967
Bank Deposit Ratio		0.11	0.111
Bank Provisions to RWA		–2.727	–2.654
Bank Liquid Asset Ratio		0.404	0.538
Bank ROA		–2.506	–3.762
Constant	4.343***	118.6	152.8

(*continued*)

Table 5. (Continued)

Variables	C&I Loan Commitment Growth Rate Perc. Pts. (Annualized) (1)	(2)	(3)
Observations	465,971	465,971	407,566
R-squared	0.299	0.299	0.312
Bank-Firm FE	Y	Y	Y
FirmSize-Industry-County-Date FE	Y	Y	Y
No. of Banks	16	16	16
No. of Firms	43,487	43,487	38,476

Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This table reports the regression results for panel data specification (2), focusing on young relationship firms. The interaction coefficient captures the differential impact that a low capital headroom bank has on annualized commitment growth rates (along the intensive margin) to young relationship firms (as compared to that of a high capital headroom bank) after the 2020:Q1 arrival of the pandemic. *Post* is a dummy variable denoting 2020:Q1 and after. *LowCapitalHeadroomBank* is a 0/1 variable denoting if the firm borrows from a lender whose CET1 capital ratio was relatively close to the costly regulatory capital buffer threshold (headroom $\leq$ 2.14 percent) as of 2019:Q4. *YoungRelationshipFirm* is a 0/1 variable denoting if the firm's relationship with its lender (as of 2019:Q4) is smaller than the median relationship age in the sample (six years). Controls include lagged firm- and bank-level characteristics. All specifications are at the bank-firm-date level, span 2018:Q1–2020:Q3, and include bank*firm as well as firm-size-decile*industry*county*date fixed effects. Standard errors are clustered by bank-date and firm. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

from Table 8 embeds the fact that the largest difference-in-difference employment growth effect occurs in the month of May 2020, where industry-counties exposed to low capital headroom banks experienced 6 percentage points slower annualized employment growth (Figure 10). It is also interesting to note that the real effects appear to be large but short term in nature (lasting three months, from May through July of 2020), consistent with the notion illustrated in Figure 3 that the balance sheet constraints and costs emanating from buffer usability were binding in the short term but not in the

Table 6. Differential Credit Effect of Low vs. High Capital Headroom Banks to Firms with Pre-existing Credit Lines Set to Mature at the Peak of the Pandemic—Borrower Exits

Variables	Pr(Borrower Exits during Pandemic)		
	(1)	**(2)**	**(3)**
FirmCredLine Maturingin Pandemic	00422***	0.00713	0.0132
LowCapitalHeadroomBank*FirmCredLineMaturinginPandemic	**0.148*** **	**0.150*** **	**0.0965*** **
LowCapitalHeadroom Bank	0.00968	0.0122	0.0233
Firm Log Assets			–0.0166***
Firm ROA			–0.0503***
Firm Leverage			–0.0533***
Firm Sales Ratio			–0.00377***
Firm Non-investment Grade Rating			0.0463***
Bank MLSP Total Loans to Assets		0.00257***	0.00169**
Bank MLSP State-Level Loans to Assets		–0.00265***	–0.00264***
Bank Undrawn Credit Line Ratio		–0.00308***	–0.00442***
Bank Log Assets		–0.00120	–0.0197***
Bank Deposit Ratio		–0.000935***	0.000170
Bank Provisions to RWA		0.0500	0.0437
Bank Liquid Asset Ratio		0.00140	0.00407***
Bank ROA		0.0596*	0.100***
Constant	0.114***	0.201**	0.730***

(*continued*)

Table 6. (Continued)

	Pr(Borrower Exits during Pandemic)		
Variables	**(1)**	**(2)**	**(3)**
Observations	46,042	46,042	39,883
R-squared	0.237	0.239	0.254
FirmSize-Industry-County FE	Y	Y	Y
No. of Banks	16	16	16
No. of Firms	33,259	33,259	28,476

Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This table presents the regression results for the cross-sectional specification (1), focusing on firms with pre-existing credit lines that were set to mature at the peak of the pandemic. All observations are as of 2019:Q4. The left-hand-side variable is a dummy variable that equals 1 if a given firm no longer exists in the FR Y-14Q at the end of the sample period (2020:Q3). The interaction coefficient captures the differential impact that a low capital headroom bank has on the probability that a firm (whose pre-existing credit line was set to mature during the pandemic) exits during the pandemic (as compared to that of a high capital headroom bank). *LowCapitalHeadroomBank* is a 0/1 variable denoting if the firm borrows from a lender whose CET1 capital ratio was relatively close to the costly regulatory capital buffer threshold (headroom $\leq$ 2.14 percent) as of 2019:Q4. *FirmCredLineMaturinginPandemic* is a 0/1 variable denoting if any portion of the firm's pre-existing credit lines (as of 2019:Q4) was set to mature at the height of the pandemic (2020:Q2). Controls include firm- and bank-level characteristics. All specifications include fixed effects for firm-size-decile*industry*county. Standard errors are clustered at the firm level. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

long term, as banks were quick to replenish their headroom beyond pre-pandemic levels within a few quarters.

In summary, we find evidence that low capital headroom banks cut lending disproportionately to private SMEs, young relationship firms, and firms whose prior credit lines were set to mature at the peak of the pandemic (and thus were up for renegotiation). Altogether, these findings are consistent with the idea that a low capital headroom bank optimizes how best to curtail credit by choosing firms for which it is least costly to curtail lending to (even though

Table 7. Differential Credit Effect of Low vs. High Capital Headroom Banks on Firms with Pre-existing Credit Lines Set to Mature at the Peak of the Pandemic—Intensive Margin

	C&I Loan Commitment Growth Rate Perc. Pts. (Annualized)		
Variables	**(1)**	**(2)**	**(3)**
*Post*LowCapital HeadroomBank*	–1.680	–2.536	–2.212
Post*LowCapital HeadroomBank* FirmCredLine Maturingin Pandemic	**–36.47*****	**–36.48*****	**–33.80*****
*2020Q1*FirmCredLine MaturinginPandemic*	–4.844	–4.656	–5.939
Firm Log Assets			–1.949***
Firm ROA			3.827*
Firm Leverage			–11.19***
Firm Sales Ratio			0.636***
Firm Non-investment Grade Rating			–1.756***
Bank MLSP Total Loans to Assets		–0.341	–0.310
Bank MLSP State-Level Loans to Assets		0.662***	0.758***
Bank Undrawn Credit Line Ratio		–0.536	–0.772**
Bank Log Assets		–5.842	–5.765
Bank Deposit Ratio		0.230	0.199
Bank Provisions to RWA		–4.838	–5.553*
Bank Liquid Asset Ratio		0.303	0.418
Bank ROA		0.756	–0.242
Constant	4.638***	106.8	146.4

(*continued*)

Table 7. (Continued)

Variables	**C&I Loan Commitment Growth Rate Perc. Pts. (Annualized)** (1)	(2)	(3)
Observations	413,953	413,953	365,482
R-squared	0.295	0.295	0.309
Bank-Firm FE	Y	Y	Y
FirmSize-Industry-County-Date FE	Y	Y	Y
No. of Banks	16	16	16
No. of Firms	34,872	34,872	31,755

Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This table reports the regression results for panel data specification (2), focusing on firms with pre-existing credit lines that were set to mature at the peak of the pandemic. This captures the relative differences across low versus high capital headroom banks in terms of annualized loan commitment growth rates (along the intensive margin) to firms whose pre-existing credit lines were set to mature during the pandemic. *Post* is a dummy variable denoting 2020:Q2. *LowCapitalHeadroomBank* is a 0/1 variable denoting if the firm borrows from a lender whose CET1 capital ratio was relatively close to the costly regulatory capital buffer threshold (headroom $\leq$ 2.14 percent) as of 2019:Q4. *FirmCredLineMaturinginPandemic* is a 0/1 variable denoting if any portion of the firm's pre-existing credit lines (as of 2019:Q4) was set to mature at the height of the pandemic (2020:Q2). Controls include lagged firm- and bank-level characteristics. All specifications are at the bank-firm-date level, span 2018:Q1–2020:Q3, and include bank*firm as well as firm-size-decile*industry*county*date fixed effects. Standard errors are clustered by bank-date and firm. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

the firm is creditworthy), suggesting that regulatory buffers do not appear to be currently working as intended.

We can construct an estimate for the economic magnitude of the credit supply shock associated with usability of regulatory buffers by summing USD amounts for the credit adjustment for the intensive margin and borrower exit analyses. For the first component, our baseline estimate from Table 3, column 3, states that low capital headroom banks curbed lending to SMEs by roughly 10.3

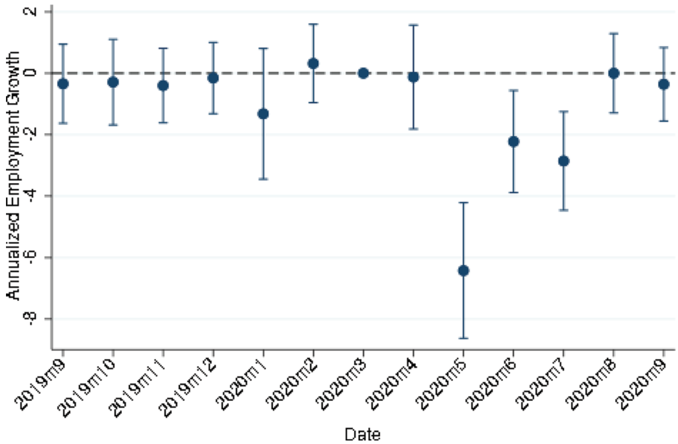
Table 8. Real Effects—Impact of Bank Capital Headroom on Industry-County Employment Growth

Variables	**Employment Growth Rate (Annualized)**
LowCapHeadroomBank Exposure	–0.214
Post*LowCapHeadroom BankExposure	**–1.867*****
Constant	10.07***
Observations	4,090,347
R-squared	0.265
Industry-Date FE	Y
County-Date FE	Y

Source: FR Y-14Q H1 Schedule, BLS QCEW, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This table reports the regression results for the employment growth regression in specification (3). Observations are at the industry-county-month level. Bank-firm loan exposures ex ante to the arrival of the pandemic (2019:Q4) are aggregated to the industry-county level and merged to the monthly employment growth rates reported in the Bureau of Labor Statistics Quarterly Census of Employment and Wages. *Post* is a 0/1 variable denoting if the date is April 2020 or later. *LowCapHeadroomBankExposure* is a 0/1 variable denoting if a given industry-county has non-zero ex ante credit exposure to a low capital headroom lender as of 2019:Q4. County-date and industry-date fixed effects are included. Standard errors are clustered at the county level. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

percentage points more (annually) during the pandemic. For the second component, the baseline estimate from Table 2, column 3 shows that SMEs borrowing from low capital headroom banks were 11.1 percent more likely to exit the FR Y-14Q during the pandemic. The total number of SME borrowers associated with low capital headroom banks in the FR Y-14Q H1 Schedule as of 2019:Q4 was 14,155 SMEs comprising \$64.8 billion in total commitments. To establish an economic magnitude of the usability of regulatory capital buffers, we estimate that the associated credit supply shock resulted in up to roughly 1,571 SME exits (= 14155*0.111) across a diverse set of industries, comprising a credit contraction between \$6.6 billion and

Figure 10. Bank Capital Headroom and Local Employment Growth



Source: FR Y-14Q H1 Schedule, Bureau of Labor Statistics Quarterly Census of Employment and Wages, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This chart shows the time-specific difference-in-difference coefficients $\beta_{2,\tau}$ (along with 90 percent confidence intervals) after estimating a modified version of specification (3), where the *Post* dummy is replaced with month-specific time dummies. These coefficients capture the relative difference each month in employment growth in industry-counties with non-zero ex ante credit exposures to low capital headroom banks (as of 2019:Q4) versus those without such ex ante exposures. Low capital headroom banks are lenders that start the pandemic with a capital ratio relatively close to the regulatory buffer threshold.

\$13.8 billion in total USD commitments.[28] In aggregate, this credit effect comprises anywhere from 10.2 percent (=\$6.6B/\$64.8B) to 21.3 percent of total SME commitments (=\$13.8B/\$64.8B).

6. Robustness Results

In this section, we test the robustness of our results in Section 5. For each test, our central result holds: low capital headroom

[28] \$6.6 Billion = \$64.8 Billion*0.103 (intensive margin), and \$13.8 Billion = \$64.8 Billion*0.103 (intensive margin) + 64.8 Billion*0.111 (borrower exit). The range is due to the fact that the borrower exit estimate of 11.1 percent is an upper-bound estimate of the extensive margin.

Table 9. Differential Credit Effect of Low vs. High Capital Headroom Banks on SMEs Excluding Smallest Firms—Intensive Margin

	C&I Loan Commitment Growth Rate Perc. Pts. (Annualized)		
Variables	**(1)**	**(2)**	**(3)**
*Post*LowCapital HeadroomBank*	1.319	0.202	0.119
Post*LowCapital HeadroomBank* PrivateSME	**–10.41*****	**–10.80*****	**–10.95*****
*Post*PrivateSME*	4.814*	5.197**	5.309*
Firm ROA			1.549
Firm Leverage			–12.22***
Firm Sales Ratio			0.733***
Firm Non-investment Grade Rating			–2.075**
Bank MLSP Total Loans to Assets		0.02	0.2
Bank MLSP State-Level Loans to Assets		0.473**	0.560**
Bank Undrawn Credit Line Ratio		–0.903***	–1.090***
Bank Log Assets		–5.764	–6.317
Bank Deposit Ratio		0.0767	0.0156
Bank Provisions to RWA		–1.437	–1.648
Bank Liquid Asset Ratio		0.447	0.564
Bank ROA		–2.965	–3.974
Constant	5.335***	117.1	135.4

(*continued*)

Table 9. (Continued)

Variables	C&I Loan Commitment Growth Rate Perc. Pts. (Annualized) (1)	(2)	(3)
Observations	375,603	375,603	333,877
R-squared	0.309	0.31	0.321
Bank-Firm FE	Y	Y	Y
FirmSize-Industry-County-Date FE	Y	Y	Y
No. of Banks	16	16	16
No. of Firms	30,763	30,763	28,053

Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This robustness table reports the regression results for panel data specification (2), focusing on SMEs, while dropping all observations that contain borrowers in the lowest decile of the firm size distribution. The interaction coefficient captures the differential impact that a low capital headroom bank has on annualized commitment growth rates (along the intensive margin) to private SMEs (as compared to that of a high capital headroom bank) after the 2020:Q1 arrival of the pandemic. *Post* is a dummy variable denoting 2020:Q1 and after. *LowCapitalHeadroomBank* is a 0/1 variable denoting if the firm borrows from a lender whose CET1 capital ratio was relatively close to the costly regulatory capital buffer threshold (headroom $\leq$ 2.14 percent) as of 2019:Q4. *PrivateSME* is a 0/1 variable denoting if the firm is private and is smaller than the median firm size in the sample, and excludes commitments that are within the first decile. Controls include lagged firm- and bank-level characteristics. All specifications are at the bank-firm-date level, span 2018:Q1–2020:Q3, and include bank*firm as well as firm-size-decile*industry*county*date fixed effects. Standard errors are clustered by bank-date and firm level. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

banks disproportionately reduced their lending to SMEs, firms with recently established lending relationships, and firms with credit lines that expired at the onset of the pandemic.

Table 9 includes robustness results for our estimates of Equation (2) by excluding firms with commitment amounts in the lowest decile of the commitment distribution. By performing this robustness test, we assess whether our results are potentially driven by firms near the $1 million reporting cutoff in the FR Y-14Q data. In other words, we drop all observations with commitment amounts less than \$1.3 million. The third column of Table 9, which includes all controls and fixed effects, shows that the coefficient estimate on the triple interaction term is −10.95 percent and remains statistically significant.[29]

Table 10 includes an interaction term between borrowers' credit quality and low capital headroom banks. To test whether our results are robust to firm credit risk, we include an additional triple interaction term (*Post*LowCapitalHeadroomBank*NonInvestment GradeFirm*) in Equation (2) to assess whether an alternative story about credit risk could be driving our results. To this end, we define *NonInvestmentGradeFirm* as a dummy variable equal to 1 if the credit rating assigned to a given borrower is BB or lower. We find that our key coefficient of interest, (*Post*LowCapitalHeadroom Bank*PrivateSME*), remains economically and statistically significant, even after incorporating this interacted firm credit risk control variable into the regression. This suggests that low capital headroom banks curtail their lending to SMEs, even after controlling for differences in firm credit risk.[30]

Table 11 presents results from an additional robustness exercise that performs a placebo test. This test takes the baseline regression from Table 3 and uses only the pre-pandemic period subsample (2018–19). We define a placebo dummy, *PostPlacebo2019*, which is equal to 1 in 2019 and 0 in 2018. As expected, Table 11 shows that our key coefficient of interest (*PostPlacebo2019*LowCapitalHeadroomBank*PrivateSME*) is neither economically nor statistically significant. This suggests that the results from our baseline regression in Table 3 constitute a result triggered by the pandemic, and not some other macro event.

Table 12 shows a robustness exercise that explores whether our baseline result from Table 3 about the declines in credit growth due to buffer usability survives an interacted control for lending to firms in COVID-affected industries. We measure an industry's COVID exposure by utilizing CRSP firm stock price data of firms to calculate the cumulative abnormal stock return for various industry

[29]This also holds for the borrower exit analysis. Results are available upon request.

[30]Results are also robust to using firm credit rating instead of an investment versus non-investment-grade dummy. Results are available upon request.

Table 10. Differential Credit Effect of Low vs. High Capital Headroom Banks on SMEs Including Credit Risk—Intensive Margin

Variables	C&I Loan Commitment Growth Rate Perc. Pts. (Annualized)		
	(1)	**(2)**	**(3)**
*Post*LowCapital HeadroomBank*	3.058	1.976	2.060
Post*LowCapital HeadroomBank* PrivateSME	**–8.410*****	**–8.639*****	**–9.258*****
*Post*NonInvest mentGradeFirm*	–2.502*	–2.553**	–2.631**
*Post*LowCapital HeadroomBank* NonInvestment GradeFirm*	–3.089*	–3.020*	–3.192*
*Post*PrivateSME*	4.217*	4.489**	4.696*
*PrivateSME*Non InvestmentGrade Firm*	0.917	0.992	2.800
Firm ROA			3.154
Firm Leverage			–10.83***
Firm Sales Ratio			0.603***
Firm Non-investment Grade Rating	–0.444	–0.553	–1.255
Bank MLSP Total Loans to Assets		–0.180	–0.00440
Bank MLSP State-Level Loans to Assets		0.539***	0.600***
Bank Undrawn Credit Line Ratio		–0.734**	–0.954***
Bank Log Assets		–5.647	–5.906
Bank Deposit Ratio		0.0587	0.00290
Bank Provisions to RWA		–1.978	–2.088

(*continued*)

Table 10. (Continued)

Variables	C&I Loan Commitment Growth Rate Perc. Pts. (Annualized)		
	(1)	**(2)**	**(3)**
Bank Liquid Asset Ratio		0.506	0.634*
Bank ROA		–2.272	–3.081
Constant	4.641***	111.0	120.9
Observations	413,953	413,953	365,854
R-squared	0.294	0.294	0.308
Bank-Firm FE	Y	Y	Y
FirmSize-Industry-County-Date FE	Y	Y	Y
No. of Banks	16	16	16
No. of Firms	34,872	34,872	31,764

Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This robustness table reports the regression results for panel data specification (2), focusing on SMEs, while more closely controlling for borrower credit risk. The interaction coefficient captures the differential impact that a low capital headroom bank has on annualized commitment growth rates (along the intensive margin) to private SMEs (as compared to that of a high capital headroom bank) after the 2020:Q1 arrival of the pandemic, controlling for differences in firm credit risk. *Post* is a dummy variable denoting 2020:Q1 and after. *LowCapitalHeadroomBank* is a 0/1 variable denoting if the firm borrows from a lender whose CET1 capital ratio was relatively close to the costly regulatory capital buffer threshold (headroom $\leq$ 2.14 percent) as of 2019:Q4. *PrivateSME* is a 0/1 variable denoting if the firm is private and is smaller than the median firm size in the sample. Controls include lagged firm- and bank-level characteristics. In this robustness exercise, we include a separate interaction term that controls for borrower credit risk, via a dummy variable for non-investment-grade borrower credit rating. All specifications are at the bank-firm-date level, span 2018:Q1–2020:Q3, and include bank*firm as well as firm-size-decile*industry*county*date fixed effects. Standard errors are clustered by bank-date and firm level. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

portfolios upon the emergence of the COVID pandemic (February 19 to March 23, 2020). Specifically, Table 12 takes Equation (2) and adds a triple interaction term (*Post*LowCapitalHeadroomBank*BorrowerIndustryPandemicCAR*) to test whether our main baseline

Table 11. Differential Credit Effect of Low vs. High Capital Headroom Banks on SMEs—Placebo Test

Variables	C&I Loan Commitment Growth Rate Perc. Pts. (Annualized) (1)	(2)	(3)
*PostPlacebo2019*Low CapitalHeadroomBank*	0.162	–0.435	–0.323
PostPlacebo2019*Low CapitalHeadroom Bank*PrivateSME	**0.272**	**0.558**	**0.828**
PostPlacebo2019 PrivateSME*	–1.256	–1.358	–0.00516
Firm ROA			1.361
Firm Leverage			–13.01***
Firm Sales Ratio			0.708***
Firm Non-investment Grade Rating			–3.304***
Bank Undrawn Credit Line Ratio		–2.499**	–2.813***
Bank Log Assets		–8.716	–14.18
Bank Deposit Ratio		–0.0129	–0.00691
Bank Provisions to RWA		6.075	1.736
Bank Liquid Asset Ratio		0.596	0.712
Bank ROA		–7.834	–7.636
Constant	6.712***	203.4	320.7
Observations	291,688	291,688	255,148
R-squared	0.317	0.318	0.327
Bank-Firm FE	Y	Y	Y
FirmSize-Industry-County FE	Y	Y	Y
No. of Banks	16	16	16
No. of Firms	31,012	31,012	26,730

(*continued*)

Table 11. (Continued)

Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This table reports the robustness tests for panel data specification (2), focusing on a placebo test during the pre-pandemic period. Specifically, we arbitrarily define 2018:Q1–2018:Q4 as the pre-placebo period and 2019:Q1–2019:Q4 as the post-placebo period. The pandemic (2020) observations have been excluded. The key triple interaction term captures the differential effect in annualized loan commitment growth rates (along the intensive margin) to private SMEs from low versus high capital headroom banks during the 2019 placebo period. *PostPlacebo2019* is a dummy variable denoting the period of 2019:Q1 to 2019:Q4. Controls include lagged firm- and bank-level characteristics. All specifications are at the bank-firm-date level, span 2018:Q1–2019:Q4, and include bank*firm as well as firm-size-decile*industry*county*date fixed effects. Standard errors are clustered by bank-date and firm level. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

results may alternatively be driven by a story of banks divesting from borrowers in industries *directly* affected by COVID (COVID-exposed). We find that our key coefficient of interest (*Post*Low CapitalHeadroomBank*PrivateSME*) remains economically and statistically significant, even after incorporating this interacted control for COVID-exposed industries.

7. Policy Discussion

As described in the Introduction and Section 3, regulatory capital buffers are soft-mandate requirements, where banks are allowed to dip into but will incur penalties and costs for doing so. While our results point to the notion that banks find these regulatory capital buffers costly to use, potential discussion about policy recommendations would first require an exploration of *why* buffer usage is costly from the banks' perspective. In particular, there are at least three potential costs. Firstly, payout restrictions associated with the usage of buffers means banks face potential market stigma.[31] Secondly, dipping into the buffer may lead to the possibility of a downgrade from

[31] For example, Andreeva, Bochmann, and Couaillier (2020) suggest that financial market pressure may have been an impediment to the usability of regulatory capital buffers for European banks.

Table 12. Differential Credit Effect of Low vs. High Capital Headroom Banks on SMEs, Controlling for COVID-Exposed Industries—Intensive Margin

	C&I Loan Commitment Growth Rate Perc. Pts. (Annualized)		
Variables	**(1)**	**(2)**	**(3)**
*Post*LowCapital HeadroomBank*	3.326*	2.240	2.417*
Post*LowCapital HeadroomBank* PrivateSME	**–9.300*****	**–9.543*****	**–10.28*****
*LowCapitalHeadroom Bank*Borrower IndustryPandemic CAR*	–0.536	–0.546	–0.642
*Post*LowCapital HeadroomBank* BorrowerIndustry PandemicCAR*	0.195*	0.191**	0.201**
*Post*PrivateSME*	4.788**	5.070**	5.336**
Firm ROA			3.185
Firm Leverage			–10.90***
Firm Sales Ratio			0.599***
Firm Non-investment Grade Rating			–1.778**
Bank MLSP Total Loans to Assets		–0.0711	0.147
Bank MLSP State-Level Loans to Assets		0.529***	0.582**
Bank Undrawn Credit Line Ratio		–0.730**	–0.951***
Bank Log Assets		–5.921	–6.251
Bank Deposit Ratio		0.0449	–0.0111
Bank Provisions to RWA		–1.865	–2.025
Bank Liquid Asset Ratio		0.494	0.617*

(*continued*)

Table 12. (Continued)

Variables	C&I Loan Commitment Growth Rate Perc. Pts. (Annualized)		
	(1)	**(2)**	**(3)**
Bank ROA		–2.444	–3.268
Constant	0.836	114.0	126.3
Observations	413,953	413,953	365,854
R-squared	0.294	0.294	0.307
Bank-Firm FE	Y	Y	Y
FirmSize-Industry-County FE	Y	Y	Y
No. of Banks	16	16	16
No. of Firms	34,872	34,872	31,764

Source: FR Y-14Q H1 Schedule, CRSP stock price data, authors' calculations.
Note: This table reports the robustness tests for panel data specification (2), controlling for the possibility that banks might have divested credit away from borrowers in industries that were negatively affected by the COVID pandemic. This captures the differential effect in annualized loan commitment growth rates (along the intensive margin) to private SMEs between low and high capital headroom banks after the 2020:Q1 arrival of the pandemic, controlling for any lending effects related to the deterioration in borrower industries directly exposed to the COVID shock. *Post* is a dummy variable denoting 2020:Q1 and after. *LowCapitalHeadroomBank* is a 0/1 variable denoting if the firm borrows from a lender whose CET1 capital ratio was relatively close to the costly regulatory capital buffer threshold (headroom $\leq$ 2.14 percent) as of 2019:Q4. *PrivateSME* is a 0/1 variable denoting if the firm is private and is smaller than the median firm size in the sample. Controls include lagged firm- and bank-level characteristics. To control for any contractions in lending due to COVID-related industry-specific shocks, we add an interaction term that includes a measure of how exposed different industries were to COVID-related revenue shocks. Specifically, we calculate the cumulative abnormal return (February 19 to March 23, 2020) for different firm industries using CRSP stock price data. All specifications are at the bank-firm-date level, span 2018:Q1–2020:Q3, and include bank*firm as well as firm-size-decile*industry*county*date fixed effects. Standard errors are clustered by bank-date and firm level. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

credit rating agencies.[32] For example, during April 2020, Moody's released a statement that global investment banks are expected to

[32]Behn, Rancoita, and Rodriguez d'Acri (2020) suggest management buffers may also matter for bank credit ratings, which is associated with a major worsening of banks' access to external funding markets.

Table 13. Abnormal Stock Price Reaction to Dividend Cuts Using a (–1,1) Event Window

	Dividend Cut Events	(–1,1) CAR Percent
All	42	–2.34 Percent**
Normal Times	12	–1.07 Percent
GFC Crisis	28	–2.88 Percent**

maintain solid capital buffers *at or above 2019 levels*.[33] The actions of credit rating agencies can have unintended externalities for the usability of regulatory capital buffers. Thirdly, buffer usage also triggers bonus restrictions with respect to bank executive compensation. Data limitations prevented prior studies from pinning down why capital buffers are costly. While this task is not empirically possible to pin down in the context of the pandemic either, below we provide some historical evidence on the first two costs.

To test the impact of market stigma related to a reduction in dividends, we use daily stock price data from 1990 to the present to conduct an event study using a Fama-French three-factor model. For each dividend cut event i, we estimate coefficients for the Fama-French three-factor model in a 120-day estimation window (130 days before to 10 days before event) as shown in Equation (4).

$$R_{it} = \beta_i + \gamma_{it}(Mkt - Rf)_t + \alpha_2 HML_t + \tau_3 SMB_t + \varepsilon_{it} \qquad (4)$$

We then use these coefficients to extract the abnormal stock return of bank i using a $(-1{,}1)$ three-day event window around the dividend cut. We find that bank dividend cut events are associated with negative cumulative abnormal stock returns (288 basis points) for banks during stress events such as the 2007–08 global financial crisis (see Table 13).

We also conduct a second event study, using bank credit rating downgrade events from 1990 to present. Overall, we find that credit rating downgrades (specifically in the 2008 crisis) led to negative

[33]See Moody's (2020).

Table 14. Abnormal Stock Price Reaction to Credit Rating Downgrades Using a (–1,1) Event Window

	Ratings Downgrade Events	(–1,1) CAR Percent
All	122	–1.29 Percent***
Normal Times	73	–0.43 Percent
GFC Crisis	48	–2.65 Percent***

cumulative abnormal returns of roughly 265 basis points during the three-day event window (see Table 14).

The costs associated with rating downgrades and dividend cuts during the GFC are economically large. Despite the potential caveats associated with the limited number of these events, these historical estimates suggest that the potential costs banks would have faced had they dipped into their regulatory capital buffers during the pandemic may have been sizable.

Due to data limitations, proposing specific policy remedies requires making strong assumptions about which of these proposed channels for the costliness of buffers was most binding for banks. The large abnormal returns associated with dividend cuts and ratings downgrades suggest it is not possible to eliminate either channel from consideration. However, there are a few policy insights that do emerge from our paper. Firstly, regulatory capital buffers appear to be acting as a kind of "double-edged" policy sword, where the costliness of regulatory capital buffers that incentivized banks to raise their CET1 ratios to historically high levels *during normal times* likely also made buffers *difficult to use during the downturn.* Secondly, potential policy recommendations include improving the transparency of the buffer requirement to reduce market stigma—for example, reassuring market participants and credit rating agencies that bank decisions to dip into their buffers do not necessarily signal weakness—or providing temporarily relief from the buffer constraint in downturns. However, beyond this, there has been evidence suggesting that the action of releasing regulatory buffers in a downturn may not necessarily lead to more *usable* capital, but rather may come with additional unanticipated costs. In particular, on March

12, 2020, the European Central Bank (ECB) posted a press release that allowed banks to operate temporarily below the level of capital defined by the Pillar 2 guidance (P2G) and the capital conservation buffer.[34] Out of the 115 euro zone banks supervised by the ECB, it is reported that only 9 banks took advantage of this relief measure. A possible reason for this reluctance, as proposed by Arnold (2021), is that "some banks have been reluctant to do so, worrying about how long the relief will last and the risk of stigma among investors." This points to the notion that *forward guidance uncertainty* may be a key friction associated with banks' incentive to use buffer relief. Corroborated by analysis done in the GFSR (IMF 2021), banks may not take advantage of the buffer relief if clear forward guidance is not provided on how long it will last.

In other words, without a specified time frame, banks may be hesitant to use the relief, as they could be forced to replenish capital at an unknown future date when the cost of capital is not ideal.

8. Conclusion

Sitting on top of minimum capital requirements, regulatory capital buffers introduced after the 2008 financial crisis are costly regions of "rainy-day" equity capital designed to absorb losses and support lending in a downturn. Although the implementation of these Basel III regulatory buffers played a key role in helping build banking system capital to historic levels, it appears this stockpile of capital went effectively unused during the pandemic. Our results suggest that banks were reluctant to use their regulatory buffers to absorb pandemic losses, and instead curtailed lending to SMEs during the pandemic.

To explore this, we employ a novel set of confidential, supervisory loan-level data between the largest U.S. banks and their corporate borrowers during the pandemic. The vast coverage of this data provides us with a unique ability to observe the lending outcomes at an important yet understudied segment of the economy, namely, private

[34]See ECB (2020). Unlike the European capital standards, the U.S. standards do not include a Pillar 2 guidance. The ECB's capital relief would have been equivalent to allowing banks to temporarily operate below the combined buffer requirements.

SMEs, whose survival was particularly dependent on financing from banks.

Controlling for borrower risk, we find that "low capital headroom banks" (e.g., lenders that entered the pandemic with a capital ratio relatively close to the regulatory buffer region) curtailed commitments to creditworthy SMEs along the intensive margin by 10.3 percent more than "high capital headroom" banks (e.g., lenders that entered the pandemic with a capital ratio relatively far from the regulatory buffer region). It also resulted in an 11.1 percent higher probability of borrower exits for low capital headroom banks. We further find heterogeneous effects across borrower type. Specifically, our results show that low capital headroom banks disproportionately curtailed lending to (i) private SMEs (while leaving valuable lending relationships with large public clients untouched), (ii) firms that had a relatively young lending relationship with their bank, and (iii) firms whose pre-pandemic credit lines contractually matured at the peak of the pandemic (and thus were up for renegotiation). These results are consistent with banks choosing cost-efficient ways of deleveraging, rather than utilizing the regulatory capital buffers for their intended purpose of maintaining the flow of credit to creditworthy businesses in a recession. We estimate that credit effects span a diverse set of industries comprising up to 21 percent of aggregate SME credit. We also find suggestive evidence of real effects on local employment growth during the pandemic (2 percent slower annually).

Our study brings a new angle to the literature on how the pandemic transmitted shocks to SMEs—specifically, these findings uncover a novel transmission channel emanating from constraints related to bank capital which led to credit supply shocks, potentially delaying the economic recovery for private SMEs. Rather than viewing the buffers as a cushion to be drawn upon during a downturn, as intended by Basel III, banks seem to have treated regulatory buffers as de facto minimum requirements.

Appendix A. Paycheck Protection Program (PPP)

One related question that arises is whether SMEs affected by the usability of regulatory buffers were able to substitute some of the loss in funds from their FR Y-14Q lender by participating in the PPP.

We explore this possible substitution by matching borrowing firms in the FR Y-14Q to the firms that participated in the PPP, utilizing a fuzzy matching algorithm (based on the text of the firm name) after filtering potential matches based on zip code and industry NAICS.

In order to then test whether firms that experienced negative credit supply shocks (from low capital headroom banks) subsequently sourced funding from the PPP, we run the following cross-sectional specification in Equation (A.1):

$$
\begin{aligned}
&\textit{Participant in PPP}[0/1]_{f,2020} \\
&\quad = \beta_0 + \beta_1 \textit{LowCapitalHeadroomBank}[0/1]_{b,2019Q4} \\
&\qquad + \beta_2 \textit{PrivateSME}[0/1]_{f,2019Q4} \\
&\qquad + \beta_3 \textit{LowCapitalHeadroomBank}[0/1]_{b,2019Q4} * \textit{PrivateSME}[0/1]_{f,2019Q4} \\
&\qquad + \beta_F \textit{FirmControls}_{f,2019Q4} + \beta_B \textit{BankControls}_{b,2019Q4} \\
&\qquad + \alpha_{BankFEs} + \gamma_{SizeIndusCountyFEs} + \varepsilon_{bf}, \qquad \text{(A.1)}
\end{aligned}
$$

where $\textit{Participant in PPP}_{f,2020}$ is a binary variable that equals 1 if a given firm participates in the PPP. The interpretation of any given coefficient would be the impact of that particular right-hand-side variable on the probability that the firm participates in the PPP. The interaction coefficient captures the difference in the likelihood that a private SME that borrowed from a low capital headroom bank prior to the pandemic participates in the PPP during the pandemic (as compared to that of a private SME that borrows from a high capital headroom bank). We use the same firm controls, bank controls, and fixed effects as in the borrower exit analysis associated with Equation (1). The results of Table A.1 show that private SMEs borrowing from low capital headroom banks are *neither more nor less* likely to participate in the PPP as compared to private SMEs borrowing from high capital headroom banks. Thus, there is no such evidence of credit substitution effects, as the estimate for the interaction coefficient of interest is not statistically significant. Firms in the FR Y-14Q have minimum credit line balances of $1 million, which is equivalent to the 99th percentile of PPP loan volume. In other words, firms that are considered small and medium size with respect to the FR Y-14Q population of firms are still much larger than the typical firm participating in the PPP, and so it is unlikely that the PPP would have been able to compensate for the

Table A.1. Are Firms Borrowing from Low Capital Headroom Banks More Likely to Participate in the PPP?

	Pr(Firm Participates in PPP)		
Variables	**(1)**	**(2)**	**(3)**
PrivateSME	0.207***	0.190***	0.225***
LowCapitalHeadroom Bank*PrivateSME	**–0.0132**	**–0.00121**	**–0.0125**
LowCapitalHeadroomBank	–0.00453		
Firm ROA			–0.0333*
Firm Leverage			0.0287**
Firm Sales Ratio			0.00843***
Firm Non-investment Grade Rating			0.00151
Constant	0.296***	0.298***	0.258***
Observations	46,042	46,042	39,883
R-squared	0.459	0.462	0.477
Bank FE	N	Y	Y
FirmSize-Industry-County FE	Y	Y	Y
No. of Banks	16	16	16
No. of Firms	33,259	33,259	28,476

Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This table presents the regression results for the cross-sectional specification (A.1). All observations are as of 2019:Q4. The left-hand-side variable is a dummy variable that equals 1 if a given firm participates in the PPP during the pandemic. The interaction coefficient captures whether a firm borrowing from a low capital headroom bank (as opposed to a high capital headroom bank) in 2019:Q4 is more or less likely to substitute its funding by utilizing PPP financing. *LowCapitalHeadroomBank* is a 0/1 variable denoting if the firm borrows from a lender whose CET1 capital ratio was relatively close to the costly regulatory capital buffer threshold (headroom $\leq$ 2.14 percent) as of 2019:Q4. *PrivateSME* is a 0/1 variable denoting if the firm is private and is smaller than the median firm size in the sample. Controls include firm- and bank-level characteristics. All specifications include fixed effects for firm-size-decile*industry*county. Standard errors are clustered by firm. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

loss in funding due to the supply-side credit contraction associated with the usability of regulatory buffers. This lack of substitution is also consistent with our employment results from Table 8. Specifically, because firms exposed to the usability of regulatory buffers via their lenders were not able to secure alternative sources of financing, it is possible that these firms may have had to adjust by slowing employment growth during the pandemic.

Appendix B. Panel Analysis of Borrower Exits

Tables B.1 through B.3 show the results for a panel regression version of the borrower exit analysis using a triple interaction term *Post*LowCapitalHeadroomBank**θ for SMEs, firms with young lending relationships, and firms that have existing credit lines that contractually mature in the first quarter of the pandemic, respectively. The coefficient of interest on the interaction term of interest is economically and statistically significant for all three Tables B.1–B.3.

Table B.1. Differential Credit Effect of Low vs. High Capital Headroom Banks on SMEs—Borrower Exits (panel version)

Variables	Pr(Borrower Exits Next Quarter)		
	(1)	**(2)**	**(3)**
*Post*LowCapitalHeadroomBank*	–0.00109	–0.00268	–0.00579*
Post*LowCapitalHeadroomBank*PrivateSME	**0.0573*****	**0.0580*****	**0.0568*****
*Post*PrivateSME*	–0.0191**	–0.0197**	–0.0206**
Firm ROA			–0.00392
Firm Leverage			–0.00338
Firm Sales Ratio			0.000644
Firm Non-investment Grade Rating			0.00184
Bank MLSP Total Loans to Assets		–0.00280	–0.00304
Bank MLSP State-Level Loans to Assets		0.000371	–0.000391
Bank Undrawn Credit Line Ratio		–0.00134	–0.00166
Bank Log Assets		–0.000218	0.00119
Bank Deposit Ratio		0.00169*	0.00178*
Bank Provisions to RWA		0.0131	0.0151
Bank Liquid Asset Ratio		–0.00108	–0.00136*
Bank ROA		0.000415	–0.0123
Constant	0.0262***	–0.0280	–0.0476

(*continued*)

Table B.1. (Continued)

Variables	Pr(Borrower Exits Next Quarter) (1)	(2)	(3)
Observations	429,961	429,961	386,825
R-squared	0.397	0.398	0.414
Bank-Firm FE	Y	Y	Y
FirmSize-Industry-County-Date FE	Y	Y	Y
No. of Banks	16	16	16
No. of Firms	35,459	35,459	32,994

Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This table reports the regression results for panel data specification version of the cross-sectional specification (1), focusing on SMEs. The left-hand-side variable is a dummy variable that equals 1 if a given firm no longer exists in the FR Y-14Q in the next quarter. The interaction coefficient captures the differential effect that a low capital headroom bank has on the probability (each quarter) that a given private SME borrower exits during the pandemic (as compared to that of a high capital headroom bank). *Post* is a dummy variable denoting 2020:Q1 and after. *LowCapitalHeadroomBank* is a 0/1 variable denoting if the firm borrows from a lender whose CET1 capital ratio was relatively close to the costly regulatory capital buffer threshold (headroom $\leq$ 2.14 percent) as of 2019:Q4. *PrivateSME* is a 0/1 variable denoting if the firm is private and is smaller than the median firm size in the sample. Controls include lagged firm- and bank-level characteristics. All specifications are at the bank-firm-date level and include bank*firm as well as firm-size-decile*industry*county*date fixed effects. Standard errors are clustered by bank-date and firm level. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

Table B.2. Differential Credit Effect of Low vs. High Capital Headroom Banks on Young Relationship Firms—Borrower Exits (panel version)

	Pr(Borrower Exits Next Quarter)		
Variables	**(1)**	**(2)**	**(3)**
*Post*LowCapitalHeadroomBank*	0.0124**	0.0104*	0.00997
Post*LowCapitalHeadroomBank*YoungRelationshipFirm	**0.0163****	**0.0163****	**0.0139****
*Post*YoungRelationshipFirm*	0.0170***	0.0171***	0.0136***
Firm ROA			–0.0210***
Firm Leverage			–0.00456
Firm Sales Ratio			0.000443
Firm Non-investment Grade Rating			0.00196
Bank MLSP Total Loans to Assets		–0.00296	–0.00279
Bank MLSP State-Level Loans to Assets		–0.000277	–0.00133
Bank Undrawn Credit Line Ratio		–0.00324**	–0.00313**
Bank Log Assets		–4.28e-05	0.00256
Bank Deposit Ratio		0.00173	0.00169
Bank Provisions to RWA		0.00592	0.00763
Bank Liquid Asset Ratio		–0.00124	–0.00156
Bank ROA		–0.0181	–0.0220
Constant	0.0439***	0.0196	–0.0223

(*continued*)

Table B.2. (Continued)

Variables	Pr(Borrower Exits Next Quarter)		
	(1)	**(2)**	**(3)**
Observations	489,939	489,939	434,956
R-squared	0.423	0.423	0.433
Bank-Firm FE	Y	Y	Y
FirmSize-Industry-County-Date FE	Y	Y	Y
No. of Banks	16	16	16
No. of Firms	45,483	45,483	40,977

Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This table reports the regression results for the panel data specification version of cross-sectional specification (1), focusing on young relationship firms. The left-hand-side variable is a dummy variable that equals 1 if a given firm no longer exists in the FR Y-14Q in the next quarter. The interaction coefficient captures the differential effect that low capital headroom bank has on the probability (each quarter) that a given young relationship borrower exits during the pandemic (as compared to that of a high capital headroom bank). *Post* is equal to 1 for 2019:Q4 to 2020:Q2. *LowCapitalHeadroomBank* is a 0/1 variable denoting if the firm borrows from a lender whose CET1 capital ratio was relatively close to the costly regulatory capital buffer threshold (headroom $\leq$ 2.14 percent) as of 2019:Q4. *YoungRelationshipFirm* is a 0/1 variable denoting if the firm's relationship with its lender (as of 2019:Q4) is smaller than the median relationship age in the sample (six years). Controls include lagged firm- and bank-level characteristics. All specifications are at the bank-firm-date level and include bank*firm as well as firm-size-decile*industry*county*date fixed effects. Standard errors are clustered by firm. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

Table B.3. Differential Credit Effect of Low vs. High Capital Headroom Banks to Firms with Pre-existing Credit Lines Set to Mature at the Peak of the Pandemic—Borrower Exits (panel version)

	Pr(Borrower Exits Next Quarter)		
Variables	**(1)**	**(2)**	**(3)**
*Post*LowCapitalHeadroomBank*	0.0334*	0.0345*	0.0334
Post*LowCapitalHeadroomBank*FirmCredLineMaturinginPandemic	**0.0773*****	**0.0765*****	**0.0593****
*Post*FirmCredLineMaturinginPandemic*	0.00574	0.00628	0.00735
Firm ROA			–0.00418
Firm Leverage			–0.00172
Firm Sales Ratio			0.000654
Firm Non-investment Grade Rating			0.00145
Bank MLSP Total Loans to Assets		–0.00340	–0.00334
Bank MLSP State-Level Loans to Assets		–6.85e-05	–0.000757
Bank Undrawn Credit Line Ratio		–0.00236**	0.00248**
Bank Log Assets		–0.0108	–0.00743
Bank Deposit Ratio		0.000983	0.00102
Bank Provisions to RWA		0.0207	0.0220
Bank Liquid Asset Ratio		–0.000456	–0.000812
Bank ROA		–0.0241	–0.0333**
Constant	0.0265***	0.235	0.177

(*continued*)

Table B.3. (Continued)

Variables	Pr(Borrower Exits Next Quarter)		
	(1)	**(2)**	**(3)**
Observations	429,961	429,961	429,961
R-squared	0.397	0.398	0.414
Bank-Firm FE	Y	Y	Y
FirmSize-Industry-County FE	Y	Y	Y
No. of Banks	16	16	16
No. of Firms	35,459	35,459	32,994

Source: FR Y-14Q H1 Schedule, aggregated calculations using bank-specific stress capital buffer and G-SIB surcharges to calculate the capital headroom.
Note: This table reports the regression results for the panel data specification version of cross-sectional specification (1), focusing on firms with pre-existing credit lines that were set to mature at the peak of the pandemic. The left-hand-side variable is a dummy variable that equals 1 if a given firm no longer exists in the FR Y-14Q in the next quarter. The interaction coefficient captures the differential quarterly effect that a low capital headroom bank has on the probability that a firm (whose pre-existing credit line was set to mature during the pandemic) exits during the pandemic (as compared to that of a high capital headroom bank). *Post* is equal to 1 in 2020:Q1. *LowCapitalHeadroomBank* is a 0/1 variable denoting if the firm borrows from a lender whose CET1 capital ratio was relatively close to the costly regulatory capital buffer threshold (headroom $\leq$ 2.14 percent) as of 2019:Q4. *FirmCredLineMaturinginPandemic* is a 0/1 variable denoting if any portion of the firm's pre-existing credit lines (as of 2019:Q4) was set to mature at the height of the pandemic (2020:Q2). Controls include lagged firm- and bank-level characteristics. All specifications are at the bank-firm-date level and include bank*firm as well as firm-size-decile*industry*county*date fixed effects. Standard errors are clustered at the firm level. *, **, and *** denote statistical significance at 10 percent, 5 percent, and 1 percent levels, respectively.

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Bank Risk-Taking and Impaired Monetary Policy Transmission*

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How does risk-taking affect the transmission of interest rate changes into loan issuance? We study this question in a banking model with agency frictions. The risk-free rate affects bank lending via a portfolio adjustment and a loan risk channel. The former implies that the bank issues more loans when the risk-free rate falls. The latter implies that the bank may issue fewer loans because lower risk-free rates lead to higher risk-taking. Thus, the loan risk channel can counteract the portfolio adjustment channel. There exists a reversal rate, so that loan supply even contracts due to higher risk-taking. The model's implications square with recent evidence on monetary transmission.

JEL Codes: G21, E44, E52.

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1. Introduction

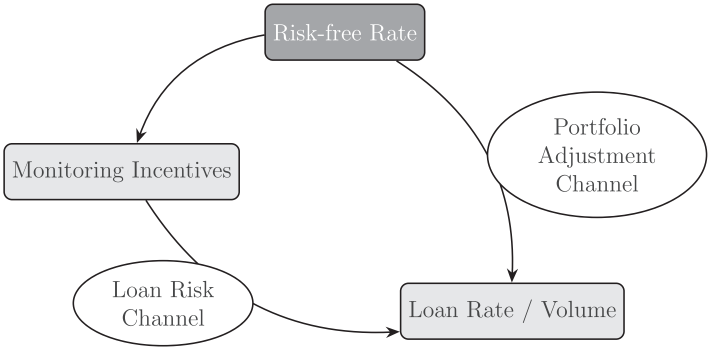
Central banks in several advanced economies have until recently kept their policy rates at historically low levels, often close to the zero lower bound. The extant literature has highlighted two key concerns on interest rate policies in such an environment. First, lower policy rates may induce banks to take more risks, which could pose a threat to financial stability (Borio and Zhu 2012). Second, lower rates could also depress bank profits to the point where banks respond less to additional monetary stimulus (Eggertsson et al. 2019) or even reduce the supply of credit to the economy (Brunnermeier, Abadi, and Koby 2023). Both phenomena have been studied in separate theoretical frameworks, but empirical evidence covering the recent period of low interest rates also suggests a close link between them, which is difficult to reconcile with existing models: the weakening of the transmission of policy rates correlates with an increase in riskier lending (Heider, Saidi, and Schepens 2019; Miller and Wanengkirtyo 2020; Arce et al. 2021).

In the present paper, we ask how such a link between impaired transmission and risk-taking can arise. We show that if deposit rates are bounded below and banks hold a sufficiently large share of fixed-income assets whose return changes with the risk-free rate, higher risk-taking and the impairment of monetary transmission can become "two sides of the same coin." In particular, if interest rates are at a sufficiently low level, further reductions of interest rates incentivize banks to increase risk-taking, which, in turn, weakens the transmission of policy rates into loan rates and loan volumes.

We consider a purposefully simple model of a penniless banker who uses deposits to fund the issuance of risky loans and the holdings of safe assets, such as bonds or central bank reserves. The banker can exert a monitoring effort to reduce the risk of default of her loan portfolio. Depositors can observe the loan issuance and the safe asset holdings of the banker. However, the monitoring effort is not observable (and hence uncontractible), thus creating an agency problem between the banker and her depositors.

In this setting, we study how changes in the risk-free rate affect loan rates and loan volumes. The transmission of the risk-free rate works via two channels, a direct portfolio adjustment channel and an indirect loan risk channel (see Figure 1).

Figure 1. Direct Portfolio Adjustment Channel and Indirect Loan Risk Channel



The portfolio adjustment channel reflects the conventional view of monetary transmission, which holds that lower risk-free rates are expansionary and translate into more bank lending. As in standard banking models, a lower risk-free rate reduces the return on safe assets and the opportunity cost of loan issuance. The banker, in turn, optimally issues more loans at lower loan rates (Freixas and Rochet 1997).

The indirect loan risk channel arises because changes in the risk-free rate also alter the banker's monitoring incentives, which, in turn, affect the banker's optimal loan issuance.[1] In particular, if monitoring incentives improve, loan risk declines and the banker optimally expands the issuance of loans by lowering the loan rate.

However, the risk-free rate exerts two opposing effects on monitoring incentives, implying that it is a priori not clear whether the loan risk channel amplifies or counteracts the portfolio adjustment channel. On the one hand, a lower risk-free rate reduces the profitability of safe assets and depresses expected profits. This *safe asset effect* worsens monitoring incentives. On the other hand, if the banker can pass on a lower risk-free rate to depositors, profits increase. This *deposit pass-through effect* improves monitoring

[1] We use the term "loan risk channel" to refer to the indirect effect of the risk-free rate on loan issuance via changes in monitoring incentives. Our loan risk channel should be distinguished from the "risk-taking channel," which refers to the direct effect of the risk-free rate on risk-taking incentives (Dell'Ariccia, Laeven, and Marquez 2014).

incentives. Whenever the safe asset effect dominates the deposit pass-through effect, the banker's monitoring incentives worsen, and her risk-taking increases when the risk-free rate becomes lower (and vice versa if the deposit pass-through effect dominates).

We show that the interaction between the portfolio adjustment channel and the loan risk channel can lead to three possible cases depending on the level of the risk-free rate.

First, if the risk-free rate is sufficiently high, the deposit pass-through effect dominates the safe asset effect, and the loan risk channel amplifies the portfolio adjustment channel. Second, for lower values of the risk-free rate, the safe asset effect dominates the deposit pass-through effect. The loan risk channel counteracts the portfolio adjustment channel. The banker still increases her loan issuance when the risk-free rate falls, but the increase in loan risk lessens her loan issuance. Third, if the risk-free rate is sufficiently low, the loan risk channel can even dominate the portfolio adjustment channel. In this case, further reductions in the risk-free rate lead the banker to reduce lending. The critical value below which the loan risk channel dominates the portfolio adjustment channel constitutes a reversal rate, as in Brunnermeier, Abadi, and Koby (2023). Like in their model, a precondition for the existence of a reversal rate is that bank profits decrease in the risk-free rate. In contrast to their model, the reversal rate in our model does not arise due to an exogenous constraint on future bank profits but stems from the agency friction between the banker and her depositors. We derive a simple condition for the occurrence of this "reversal scenario": the loan risk channel dominates the portfolio adjustment channel if the banker reduces her monitoring more than one-for-one in response to a reduction in the risk-free rate.

To simplify the exposition of the key mechanism behind the interaction of risk-taking and monetary policy transmission, we make two assumptions in our baseline model.

First, there is a lower bound on deposit rates; i.e., there exists a minimal return that the banker must offer on deposits for agents to be willing to hold them rather than switch to cash. This assumption reflects the empirical observation that changes in deposit rates become progressively smaller and approach a lower bound when policy rates are lowered towards negative territory (Eggertsson et al. 2019).

Second, the banker always holds a non-negligible amount of assets whose rate of return changes in lockstep with changes in the policy rate. We assume that these are "safe assets" such as central bank reserves, government bonds, or senior tranches of mortgage-backed securities.[2] For the safe asset effect to arise, the banker's expected profit must react sufficiently to changes in the risk-free rate. That is, the banker must be somewhat constrained in reducing her safe assets in order to mitigate (or even to offset completely) the negative effect of a lower risk-free rate on her profits. There are various reasons why banks face such constraints in practice. For example, due to setup and switching costs, deposits are a quasi-fixed factor of production (Flannery 1982; Sharpe 1997). Once banks raise deposit funding before deciding on their loan issuance, deposit and loan volumes are not necessarily completely balanced.[3] As a consequence, deposits in excess of what is required to fund loan issuance may be held as reserves with the central bank or invested in short-term fixed-income securities. In addition, banks face regulatory constraints, such as reserve or liquidity requirements, that force them to cover a certain share of their deposit liabilities with safe and liquid assets, like reserves or government bonds. Moreover, since the financial crisis of 2008/09, central banks have expanded reserves through asset purchase and lending programs beyond what is required by the banking sector in aggregate (Ennis and Wolman 2015; European Central Bank 2017; Bechtel et al. 2021). Under such a regime, individual banks may end up with excess reserves without being able to instantly dispose of reserves via the interbank market (Brandao-Marques et al. 2021).

To simplify the exposition in the baseline model, we follow Acharya and Naqvi (2012) and assume that the banker has a fixed amount of deposits and cannot adjust the "intensive margin" of her deposits. Moreover, we fix the deposit amount such that the banker

[2]We could also allow the banker to invest in risky fixed-income securities, provided that their payoffs are uncorrelated with the payoffs from the bank's loans and that a no-arbitrage condition ensures that their expected return matches the risk-free rate.

[3]In practice, banks often adjust deposit volumes by changing the rate offered on deposits. Empirically, in particular at low rates, rate adjustments and, by extensions, adjustments in deposit volumes, occur rather infrequently (Paraschiv 2013; Jobst and Lin 2016; Döpp, Horovitz, and Szimayer 2022), suggesting an imperfect adjustment between loans and deposits.

is bound to hold more deposits than what she needs to fund her optimal loan issuance. Any residual deposits are invested in safe assets whose return moves in lockstep with the risk-free rate. Put differently, although the banker can trade off loan issuance and safe assets at the margin, she cannot shrink her balance sheet by issuing fewer deposits and disposing of safe assets completely.

We consider several extensions of this baseline model to probe the robustness of its mechanism. First, we analyze the effect of insured deposits on the possibility of transmission reversal. Deposit insurance (if not fairly priced) provides an exogenous subsidy to the banker that increases her profits. As a consequence, deposit insurance mitigates the problem of transmission reversal. In the limit, when all deposits are insured, the reversal rate ceases to exist. Thus, ceteris paribus, a transmission reversal constitutes less of a problem for banks that are funded with a larger share of insured deposits.

Second, we relax the admittedly stark assumption that the banker cannot adjust the intensive margin of her deposits and the size of her balance sheet. Instead, we allow the banker to endogenously choose deposits and safe assets. We consider two variants of the model that both preserve the safe asset effect. In the first, we assume that the bank faces random inflows or outflows to depositors' accounts. These random changes to deposits are matched on the banker's balance sheet by inflows and outflows of central bank reserves. As a consequence, the bank may end up holding excess reserves with a certain probability. This extension illustrates that the presence or absence of the safe asset effect depends on the banker's ability to optimally adjust her safe asset position. In particular, we recover the results in the benchmark model if the probability of a deposit inflow (i.e., ending up with excess reserves) approaches unity, whereas the safe asset effect disappears if the probability of random reserve changes goes to zero. In the second variant, instead of random deposit flows, we assume that the banker faces a liquidity requirement that forces her to hold safe assets equal to a certain share of her deposits (as in Brunnermeier, Abadi, and Koby 2023). In this case, the portfolio adjustment and the loan risk channel always move in the same direction, but both switch signs once the safe asset effect dominates the deposit pass-through effect. The dominance of the safe asset effect becomes a necessary and sufficient condition for the reversal of monetary transmission.

Related Literature. Our paper relates to a large body of literature that analyzes the transmission of monetary policy through the banking sector. The traditional view is that a reduction in policy rates reduces banks' funding cost and induces greater loan supply (Bernanke and Blinder 1988; Bernanke and Gertler 1995; Kashyap and Stein 1995). A variant of this channel is at work in our model, but we show that it can be weakened or amplified by an (a priori) ambiguous indirect loan risk channel that arises from the agency problem between the bank and its depositors.

The loan risk channel connects our paper to the literature on the risk-taking channel of monetary policy (e.g., Dell'Ariccia, Laeven, and Marquez 2014; Martinez-Miera and Repullo 2017). The risk-taking channel refers to the direct effect of interest rate changes on the bank's monitoring incentives. We show how the presence of a lower bound on deposit rates and the presence of safe asset holdings creates a novel variant of the risk-taking channel. However, the focus of our model is on the loan risk channel, i.e., the indirect effect of the risk-free rate on loan issuance via monitoring incentives.

The banks in our model face an agency problem similar to that of Dell'Ariccia, Laeven, and Marquez (2014). In contrast to Dell'Ariccia, Laeven, and Marquez (2014), who focus on the effect of leverage, we adopt the assumption of a fixed deposit volume from Acharya and Naqvi (2012) to concentrate on the effect of monetary policy on the bank's endogenous portfolio adjustment between loans and safe assets. Our model therefore complements Dell'Ariccia, Laeven, and Marquez (2014) in two ways. Firstly, in contrast to their results, even a fully leveraged bank can increase risk-taking in response to a lower policy rate because of the interaction between the deposit pass-through and the safe asset effect. Secondly, the effect of the risk-free rate on loan rates depends on the interaction between the portfolio adjustment and the loan risk channel. This decomposition allows us to show how the transmission of policy rates can become weaker at low levels of the policy rate.[4]

The dependency of monetary transmission on the level of the policy rate connects our paper to the growing literature on monetary

[4]In Dell'Ariccia, Laeven, and Marquez (2014), the total effect of interest rates on loan rates is unambiguously positive, so that a reversal of transmission cannot arise.

policy transmission in a low interest rate environment. Eggertsson et al. (2019) argue that the increasing attractiveness of cash impairs the pass-through to deposit rates when the policy rate approaches the zero lower bound or becomes negative. Brunnermeier, Abadi, and Koby (2023) show the existence of the reversal rate below which further reductions in policy rates lead to an increase in loan rates. Eggertsson et al. (2019) and Brunnermeier, Abadi, and Koby (2023) derive their results by imposing an exogenous net worth constraint that mechanically increases equilibrium loan rates. Darracq Pariès, Kok, and Rottner (2020) study the reversal rate in a general equilibrium model with agency frictions. Their net worth constraint arises because the banker can abscond with deposits. Our model complements these papers by showing how a reversal rate can arise from an agency problem and the bank's risk-taking incentives.

Several recent papers analyze the effects of excess reserves on the determination of the price level (Ennis 2018) or the effect of bank lending (Martin, McAndrews, and Skeie 2016). Our results complement Martin, McAndrews, and Skeie (2016). They argue that reserve holdings do not matter for bank lending in a frictionless economy, but they do so in the presence of balance sheet costs. We show how excess reserves affect lending in the presence of agency frictions.

The implications of our model are in line with empirical observations at low levels of the policy rate, such as a positive relationship between bank profits and policy rates (Ampudia and Van den Heuvel 2022; Wang et al. 2022), or a negative relationship between mortgage rates and policy rates (Basten and Mariathasan 2020; Miller and Wanengkirtyo 2020). Our model suggests an explanation for higher risk-taking at rock-bottom interest rates (Heider, Saidi, and Schepens 2019; Basten and Mariathasan 2020; Bittner, Bonfim, et al. 2021), and shows why the pass-through to loans may weaken specifically for riskier banks (Arce et al. 2021).

2. Model Setup

We consider a bank over two periods, indexed by $t = 0, 1$. The bank is run by a penniless risk-neutral bank owner/manager ("banker"). The banker can obtain deposits from a large number of risk-neutral depositors. The banker decides on the issuance of loans and on the monitoring of her loans. Monitoring entails a private cost for the banker and reduces the riskiness of her loans. Depositors cannot observe the banker's monitoring choice and the banker cannot commit to a certain level of monitoring. The main focus of our analysis is on the transmission of monetary policy to loan rates, the loan volume, and the loan risk. We take the gross risk-free interest rate $r > 0$ as the measure of monetary policy and assume that it can be perfectly controlled by the central bank.

Bank Liabilities. The banker raises deposits in period 0. Deposits are uninsured and depositors must be compensated for the risk that the banker cannot fully repay depositors in period 1.[5] Thus, to attract deposits, the banker must offer a deposit rate, r_D, which, in expected terms, matches the depositors' outside option, $u(r)$.

Assumption 1. *The depositors' outside option $u(r) \geq r$ is bounded below by $\underline{u}$, i.e., $u(r) = \underline{u}$ for all $r \leq u^{-1}(\underline{u})$. For $r > u^{-1}(\underline{u})$, $u(r)$ is continuously increasing and convex; moreover, $u'(r)$ is continuous at $u^{-1}(\underline{u})$, i.e., $u'(r)$ satisfies* $\lim_{r\downarrow u^{-1}(\underline{u})} u'(r) = 0$.

The lower bound $\underline{u}$ reflects the idea that depositors would switch to other assets, such as non-interest-bearing cash holdings, once the risk-free rate becomes too low. The lower bound is not necessarily equal to zero, as negative rates could still be compensated for in the form of non-pecuniary benefits of deposits, such as the safety and ease of making payments. The lower bound on $u(\cdot)$ is the key assumption needed for the mechanism of our model, whereas the continuity and convexity assumptions are made for the sake of technical tractability and can easily be dropped (see Section 4.3).

To further simplify the exposition of the model, we assume that the banker cannot adjust the "intensive margin" of her deposits. That is, she either raises an amount D or no deposits at all. We relax this assumption in Section 4.2 where we allow the banker to choose deposits endogenously.

Assumption 2. *The amount of deposits, D, is exogenously given.*

Bank Assets and Monitoring. The banker is a monopolist in the local loan market. The demand for loans in period 0 is described

[5] Section 4.1 considers the effect when the banker also issues insured deposits.

by a demand curve $L(r_L)$, with $L'(r_L) < 0$ and $L''(r_L) \leq 0$, where r_L denotes the gross interest rate the banker charges on loans.

Loans are risky and are repaid in period 1 with probability $q \in (0, 1)$. The banker can exert unobservable monitoring effort to influence the repayment probability of her loans. We assume that monitoring translates one-to-one into the repayment probability, i.e., the banker can choose q directly. Monitoring involves a private cost[6]

$$c(q) = \frac{\kappa}{2} q^2, \quad \text{where } \kappa > 0.$$

Alternatively, the banker can invest in a risk-free asset that yields the gross risk-free return r in period 1. One can think of the risk-free asset as government bonds or reserves held with the central bank.[7] The amount invested in the risk-free asset is denoted by R.

The bank's funding constraint in period 0 is given by

$$R + L = D. \tag{1}$$

The amount invested in the risk-free asset is determined endogenously through the banker's choice of loans as the residual $R = D - L$. Henceforth, we use $\rho \equiv \frac{R}{D} = 1 - \frac{L}{D}$ to denote the share of deposits held in the risk-free asset.

We simplify the exposition of the model by imposing the following assumption on the relationship between loan issuance and the fixed deposit volume.

Assumption 3. *The elasticity of the loan demand function, $\eta(r_L) \equiv -\frac{L'(r_L) r_L}{L(r_L)}$, satisfies*

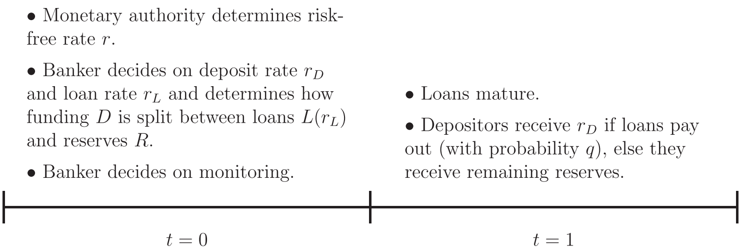
$$\eta(L^{-1}(D)) < 1.$$

Assumption 3 implies that the banker never exhausts her entire funding base to issue loans, but always holds a strictly positive

[6] For analytical tractability, we assume that monitoring costs do not depend on the banker's loan issuance. For example, $c(q)$ may represent setup costs for risk-management systems that, once in place, can be used to process a large number of loans. As we show in Appendix A.2, our results remain qualitatively unchanged if we assume a cost function that scales with the loan volume, $c(q, r_L) = \frac{\kappa}{2} q^2 L(r_L)$.

[7] The asset can be risky as long as its payoffs are not correlated with the bank loan risk and a no-arbitrage condition holds so that the asset's expected return equals the risk-free rate.

Figure 2. Sequence of Events



amount of safe assets. We relax Assumption 3 together with Assumption 2 in Section 4.2.

Sequence of Events and Equilibrium. Figure 2 shows the sequence of events in the model. An equilibrium of the model is given by a loan rate r_L^* and a deposit rate r_D^*, which jointly determine the bank's optimal loan supply, L^*, optimal safe asset holdings, R^*, and the monitoring choice, q^*. The loan rate r_L^* and the monitoring choice q^* maximize the banker's expected profits given the funding constraint (1), while the deposit rate r_D^* ensures depositor participation, given depositors' rational expectations about the bank's monitoring choice.

3. The Portfolio Adjustment and the Loan Risk Channel

Optimal Monitoring Choice. We solve the model backwards by first considering the banker's optimal choice of monitoring and then determining her optimal loan issuance. The banker's expected profits, for given r_L and R, can be written as

$$\Pi = q\left(r_L L(r_L) + rR - r_D D\right) - \frac{\kappa q^2}{2}. \tag{2}$$

The first-order condition for the optimal monitoring choice becomes[8]

$$r_L L(r_L) + rR - r_D D - \kappa \hat{q} = 0. \tag{3}$$

[8] All derivations can be found in the appendix.

Given that depositors rationally anticipate the bank's optimal monitoring choice $\hat{q}$, the interest rate on deposits that ensures depositor participation must satisfy

$$\hat{q}r_D + (1-\hat{q})\frac{rR}{D} \geq u(r). \tag{4}$$

Depositors expect to be paid r_D with probability $\hat{q}$. With converse probability, the bank defaults when loans do not pay out at maturity, and depositors obtain a senior claim over a pro rata share of the remaining safe assets. The expected repayment to the depositors must be at least as large as their outside option $u(r)$. Since the banker's expected profits are strictly decreasing in r_D, condition (4) binds at the optimum, so we can substitute

$$r_D = \frac{u(r) - (1-\hat{q})\frac{rR}{D}}{\hat{q}} \tag{5}$$

into condition (3) and solve for the optimal monitoring choice $\hat{q}$.[9]

LEMMA 1. *The banker's optimal monitoring choice is given by a function $\hat{q}(r_L, r)$ with*

$$\frac{\partial \hat{q}}{\partial r_L} \begin{cases} \geq 0 & \text{if } \frac{\hat{q}r_L - r}{\hat{q}r_L} \leq \frac{1}{\eta(r_L)} \\ < 0 & \text{else} \end{cases} \quad \text{and} \quad \frac{\partial \hat{q}}{\partial r} \begin{cases} \geq 0 & \text{if } u'(r) \leq \rho \\ < 0 & \text{else} \end{cases},$$

where $\eta(r_L) \equiv -L'(r_L)r_L/L(r_L)$ denotes the loan demand elasticity and $\rho \equiv R/D$.

The effects of r_L and r on the optimal monitoring level reflect the effects of these rates on the banker's expected profits. Whenever a marginal increase in these rates raises profits, the banker increases her monitoring and vice versa.

More specifically, a higher loan rate increases monitoring whenever the loan rate r_L is such that the Lerner index, $(\hat{q}r_L - r)/\hat{q}r$, is

[9]The equation that pins down $\hat{q}$ is quadratic and has two solutions. Following Allen, Carletti, and Marquez (2011), we choose the larger of the two roots. Moreover, as Dell'Ariccia, Laeven, and Marquez (2014), we focus on the interior solution where $\hat{q} < 1$ and abstract from the corner solution where $\hat{q} = 1$. There is a sufficiently large range of values for κ such that the interior solution exists.

lower than the inverse loan demand elasticity, $1/\eta(r_L)$, which is the standard condition for the profits of a monopolistic bank to (locally) increase in r_L (Freixas and Rochet 1997).

Whether a lower risk-free rate increases profits and leads to higher monitoring depends on the relative magnitude of two effects. On the one hand, a marginal reduction in the risk-free rate lowers the value of the depositors' outside option and thereby reduces the banker's expected deposit funding costs. This *deposit pass-through effect* increases profits by an amount $u'(r)D$ and incentivizes the banker to increase monitoring. On the other hand, a marginal reduction in the risk-free rate reduces the banker's return on safe assets. This *safe asset effect* reduces profits by R and induces the banker to reduce monitoring. Thus, a lower risk-free rate decreases monitoring if the deposit pass-through effect is smaller than the safe asset effect, i.e., if

$$u'(r)D < R \;\Leftrightarrow\; u'(r) < \rho. \tag{6}$$

Optimal Loan Issuance and Reserve Holdings. Substituting the funding constraint (1), the deposit rate (5), and the banker's optimal monitoring choice $\hat{q}(r_L, r)$ into (2) allows us to rewrite expected profits as

$$\begin{aligned} \Pi = {} & \underbrace{\hat{q}(r_L, r) r_L L(r_L)}_{\text{Expected earnings on loans.}} + \underbrace{r(D - L(r_L))}_{\text{Earnings on reserves}} - \underbrace{u(r)D}_{\text{Cost of funds}} \\ & - \underbrace{\frac{\kappa}{2}\hat{q}(r_L, r)^2}_{\text{Monitoring cost}} . \end{aligned} \tag{7}$$

The banker's remaining choice variable is the loan rate r_L. The optimal loan rate, r_L^*, is determined by the standard condition for loan issuance of a monopolistic bank: the Lerner index equals the inverse loan demand elasticity

$$\frac{\hat{q}(r_L^*, r) r_L^* - r}{\hat{q}(r_L^*, r) r_L^*} = \frac{1}{\eta(r_L^*)}. \tag{8}$$

At the optimum point, the elasticity of the loan demand exceeds unity, $\eta(r_L^*) > 1$. Condition (8) takes this particularly simple form because the effect of r_L on $\hat{q}$ can also be expressed in terms of the Lerner index and the inverse demand elasticity (cf. Lemma 1).

Monetary Policy Transmission. Monetary policy actions that change the risk-free rate affect the banker's optimal loan rate (and therefore the loan volume) through a *portfolio adjustment channel* and a *loan risk channel:*

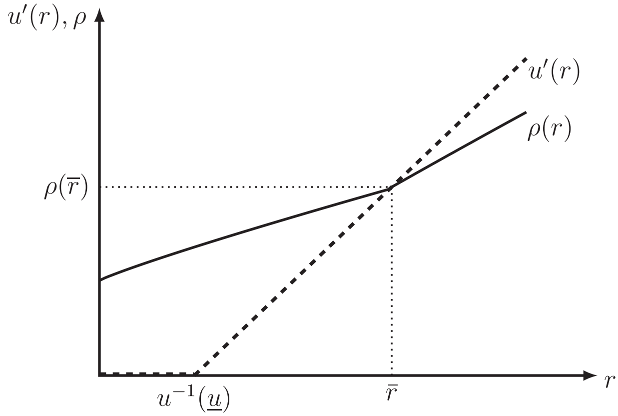
$$\frac{dr_L^*}{dr} = \underbrace{\overbrace{\frac{\partial r_L^*}{\partial r}}^{(+)}}_{\substack{\text{portfolio adjustment}\\ \text{channel}}} + \underbrace{\overbrace{\frac{\partial r_L^*}{\partial q}}^{(-)} \times \overbrace{\frac{\partial \hat{q}(r_L^*, r)}{\partial r}}^{(+)/(-)}}_{\text{loan risk channel}}. \tag{9}$$

The conventional view of monetary policy transmission holds that a lower risk-free rate is expansionary because it induces an increase in bank loan issuance. The portfolio adjustment channel reflects this conventional transmission of monetary policy. Effectively, the banker solves an optimal portfolio problem by allocating her funds between two investment opportunities (loans and safe assets).[10] Given $\hat{q}$, a lower risk-free rate reduces the opportunity cost of investing in loans rather than safe assets. As a consequence, the banker optimally reduces the loan rate and increases the amount of loan issuance.

In contrast to the portfolio adjustment channel, the effect of the loan risk channel is ambiguous: it can either amplify or dampen the portfolio adjustment channel. To understand the intuition behind the workings of the loan risk channel, note that, ceteris paribus, a lower success probability increases the loan rate and reduces the amount of loan issuance, i.e., $\partial r_L^*/\partial q < 0$. The reason is that the bank optimally reacts to a lower success probability by increasing the loan rate in order to keep the expected marginal benefit from issuing an additional loan equal to the risk-free rate that it earns on safe assets (cf. Equation (8)). Thus, whenever the safe asset

[10] Since the volume of deposits is fixed, the optimal loan rate is independent of the costs of deposits as in the textbook version of a monopolistic bank with separable loan and deposit choices (Freixas and Rochet 1997). In Section 4.2, we show two variants of the model where the banker can choose the deposit volume.

Figure 3. Required Marginal Deposit Rate, $u'(r)$, and Reserves-Deposit Ratio, ρ



Note: To the right (left) of $\overline{r}$, the loan risk channel amplifies (weakens) the portfolio adjustment channel, as can be seen from the change in the slope of the red curve at $\overline{r}$.

effect dominates, a reduction in the risk-free rate reduces monitoring, $\partial \hat{q}/\partial r > 0$, and the loan risk channel counteracts the portfolio adjustment channel, thus weakening monetary transmission.

PROPOSITION 1. *For a sufficiently small risk-free rate, the safe asset effect dominates the deposit pass-through effect and the loan risk channel weakens the transmission of monetary policy via the portfolio adjustment channel, i.e., there exists $\overline{r}$ such that*

$$r < \overline{r} \Rightarrow \frac{\partial \hat{q}}{\partial r} > 0. \tag{10}$$

Figure 3 illustrates Proposition 1. Note that the lower bound on $u(r)$ implies that for $r < u^{-1}(\underline{u})$, the deposit pass-through becomes fully impaired, i.e., $u'(r) = 0$. At this level of the risk-free rate, the banker is unable to pass a lower risk-free rate through to her depositors and she becomes unable to further reduce her expected funding costs. The dashed curve in Figure 3 shows the marginal required deposit rate, $u'(r)$, which becomes flat below $u^{-1}(\underline{u})$ when the pass-through is fully impaired. However, by Assumption 3, the banker always holds a strictly positive level of reserves, even at low risk-free rates below $u^{-1}(\underline{u})$. Thus, the safe asset effect dominates the deposit pass-through effect whenever the risk-free rate falls below $\overline{r} > u^{-1}(\underline{u})$. The solid curve shows the ratio of safe assets to deposits, evaluated at the optimal loan rate, $\rho(r) = 1 - L(r_L^*(r))/D$. For r above the critical value $\overline{r}$, the loan risk channel amplifies the portfolio adjustment channel. Below the critical value $\overline{r}$, a lower risk-free rate reduces the banker's monitoring incentives, and the loan risk channel weakens the portfolio adjustment channel.[11] The slope of the ratio of safe assets to deposits becomes less steep when $r < \overline{r}$. The reason is that, due to the counteracting loan risk channel, the interest rate reduction required to achieve a given reduction in safe assets (a given increase in loan issuance) becomes larger.

Reversal of Monetary Transmission. The loan risk channel may not only weaken the portfolio adjustment channel; it can also dominate it. In this case, a lower risk-free rate leads to an *increase* in the loan rate and a *reduction* in the bank's loan supply.

PROPOSITION 2. *The loan risk channel dominates the portfolio adjustment channel, i.e.,* $\frac{dr_L^*}{dr} < 0$, *if and only if*

$$\frac{\partial \hat{q}(r_L^*, r)}{\partial r} \frac{r}{\hat{q}(r_L^*, r)} > 1. \tag{11}$$

To understand the intuition behind Proposition 2, recall that, on the one hand, a lower success probability makes loan issuance relatively less profitable compared to holding safe assets, implying that the bank cuts back its loan issuance when q is lower. On the other hand, a lower risk-free rate reduces the return on safe assets and makes holding safe assets less profitable. If the reduction in the risk-free rate lowers the success probability and the profitability of loans by more than the profitability of reserves, the bank prefers to hold more safe assets, despite the lower risk-free rate. However, for the profitability of loans to fall by more than the profitability of safe

[11] Observe that condition (10) is only a sufficient condition. It does not rule out the possibility that the safe asset effect dominates the deposit pass-through effect at a higher level of the risk-free rate (above $\overline{r}$). Whether such a case can arise depends on the other properties of $u(r)$ and $L(r_L)$, such as the curvature or magnitude of its rate of change.

assets, the banker's monitoring must react strongly enough, i.e., a reduction in r must lead to an overproportional reduction in $\hat{q}$.

PROPOSITION 3. *If monitoring costs are sufficiently high, then the loan risk channel dominates the portfolio adjustment channel if the risk-free rate becomes sufficiently low: that is, for $\kappa > \underline{\kappa}$, there exists a critical value $\hat{r} < \bar{r}$ such that*

$$r < \hat{r} \Leftrightarrow \frac{dr_L^*}{dr} < 0.$$

The critical value $\hat{r}$ is strictly increasing in the bank's monitoring cost κ.

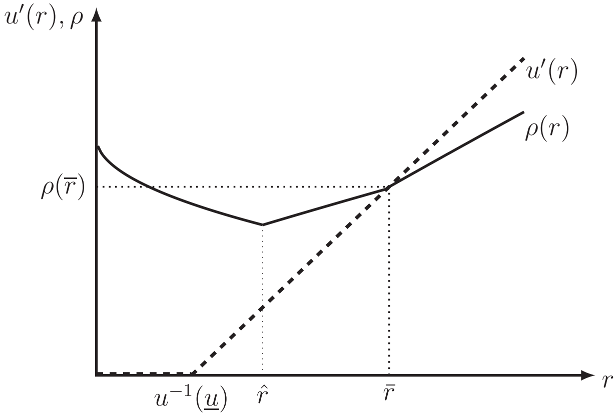
Proposition 3 translates the condition in Proposition 2 into a critical value for the risk-free rate. In particular, whenever the monitoring costs are sufficiently high and the risk-free rate falls below the critical rate, the elasticity of $\hat{q}$ becomes sufficiently large so that the loan risk channel becomes the dominant transmission channel of monetary policy. As in Brunnermeier, Abadi, and Koby (2023), below $\hat{r}$, reductions in the risk-free rate are contractionary rather than expansionary and $\hat{r}$ constitutes a *reversal rate*.

Figure 4 illustrates Proposition 3. As in Figure 3, it plots the required marginal deposit rate $u'(r)$ (dashed curve) against the ratio of safe assets to deposits, ρ (solid curve). However, in Figure 4, we assume that $\kappa > \underline{\kappa}$, so that the reserves-deposit ratio becomes downward sloping for values of r below the reversal rate $\hat{r}$. Since the reversal rate is equal to the point at which the loan risk channel just offsets the portfolio adjustment channel, it follows that the reversal rate must be strictly below the threshold $\bar{r}$.

Figure 5 summarizes our results by illustrating how the transmission of *changes* in the risk-free rate in our model depends on the prevailing *level* of the risk-free rate.

Our analysis complements Brunnermeier, Abadi, and Koby (2023) by showing that a reversal rate can arise as a consequence of banks' risk-taking behavior. The reversal rate in their model arises due to a binding exogenous constraint on future profits, whereas the reversal in our model is a consequence of the banker's endogenous risk choice that only exists if the banker increases her risk-taking sufficiently strongly in response to a change in the risk-free rate. The

Figure 4. Reversal of Transmission when $\boldsymbol{\kappa} > \overline{\boldsymbol{\kappa}}$



Note: For $r \in (\hat{r}, \overline{r})$, the loan risk channel weakens the portfolio adjustment mechanism. For $r < \hat{r}$, the loan risk channel dominates and monetary transmission reverses.

Figure 5. Monetary Transmission and the Risk-Free Rate

transmission reversal	weakened transmission	strong transmission
$\frac{r}{\hat{q}}\frac{\partial \hat{q}}{\partial r} > 1,\ \frac{dL^*}{dr} < 0$	$0 < \frac{r}{\hat{q}}\frac{\partial \hat{q}}{\partial r} < 1,\ \frac{dL^*}{dr} > 0$	$\frac{r}{\hat{q}}\frac{\partial \hat{q}}{\partial r} < 0,\ \frac{dL^*}{dr} > 0$

$\hat{r}$ $\overline{r}$

Note: The transmission of *changes* in the risk-free rate depends on the prevailing *level* of the risk-free rate. For $r > \overline{r}$, a lower risk-free rate, r, reduces risk-taking and raises loan issuance. For $r \in [\hat{r}, \overline{r}]$, a lower r raises risk-taking and weakens loan issuance. For $r < \hat{r}$, risk-taking is too strong and transmission into loans reverses.

reversal rate in our model is just the most extreme manifestation of the more general phenomenon that the loan risk channel weakens monetary transmission for sufficiently low risk-free rates.

Implications of the Model. We use Propositions 1 and 3 to derive several testable implications from our model.

HYPOTHESIS 1. *An increase in the banker's exogenous deposit funding is associated with*

- *higher safe asset holdings, higher loan rates, and a lower loan volume;*
- *higher bank risk-taking;*
- *weaker monetary policy transmission.*

Hypothesis 1 follows because an increase in the deposit volume strengthens the safe asset effect compared to the deposit pass-through effect. As a consequence, the threshold $\bar{r}$ increases, and the range of policy rates at which the loan risk channel weakens the transmission via the portfolio channel becomes larger.

Hypothesis 1 is in line with recent empirical findings of Jimenez et al. (2012), Miller and Wanengkirtyo (2020), and Bittner, Rodnyansky, et al. (2021). Note first that an increase in deposits leads to an increase in safe asset holdings, e.g., in the form of excess reserves with the central bank or government bonds. Jimenez et al. (2012) show that banks with more liquidity on their balance sheet expand the issuance of loans less after a rate cut. However, they do not distinguish between required reserves and excess reserves. Miller and Wanengkirtyo (2020) show that, following a reduction in the policy rate, banks with larger excess reserves extend lending to riskier borrowers. Bittner, Rodnyanski, et al. (2021) further provide evidence that in the presence of a zero lower bound on deposit rates, banks that depend more on deposit funding and have greater exposure to large-scale asset purchases lend relatively less and increase their risk-taking more.

HYPOTHESIS 2. *The reversal rate is larger if, ceteris paribus,*

- *the bank has more deposits;*
- *the bank is riskier, and its loan portfolio is more costly to monitor.*

Hypothesis 2 follows from the effects of leverage, and the monitoring cost parameter, κ, on the reversal rate $\hat{r}$ (cf. Proposition 3). Higher deposits (and a larger cost parameter κ) exacerbate the agency conflict and increase the banker's risk-taking incentives. Since higher risk-taking raises the loan rate for any value of r, the reversal rate (at which the loan risk channel offsets the portfolio channel) also increases.

Hypothesis 2 is in line with recent evidence by Arce et al. (2021), who show that a negative correlation between policy rate and loan rates can be found for banks that are poorly capitalized and whose lending is riskier. Similarly, Basten and Mariathasan (2020) and Miller and Wanengkirtyo (2020) find that lower policy rates are negatively correlated with mortgage rates, but not with interest rates on other types of loan. Hypothesis 2 is consistent with these findings to the extent that mortgage handling is relatively more costly than the origination and handling of other types of loans.

4. Extensions and Discussion

4.1 Insured Deposits

In this section, we consider how deposit insurance alters the transmission of monetary policy via portfolio adjustment and loan risk channels and the possibility of a transmission reversal. Suppose that a share $\delta \in [0, 1]$ of deposits is insured at a flat rate normalized to zero. For simplicity, insured depositors have the same outside option as uninsured depositors.[12]

As before, we solve the model backward by first deriving the banker's optimal monitoring choice and thereafter the optimal loan rate. The first-order condition for the monitoring choice is as in Equation (3), except that we replace the deposit rate r_D with the average deposit rate $\bar{r}_D$ which depends on the share of insured deposits. As uninsured depositors rationally anticipate bank monitoring $\hat{q}$, the average deposit rate is[13]

$$\bar{r}_D = \frac{(\delta\hat{q} + 1 - \delta)u(r) - (1 - \delta)(1 - \hat{q})\frac{rR}{D}}{\hat{q}}.$$

Substituting $\bar{r}_D$ into Equation (3) implicitly defines the banker's optimal monitoring $\hat{q}(r_L, r, \delta)$. Importantly, the condition for $\hat{q}$ to increase in r is the same as in Lemma 1,

[12] Our results remain qualitatively unchanged if insured and uninsured depositors have different outside options. We discuss this case in Appendix A.3.

[13] For simplicity, we assume that, after default at maturity, the bank's cash flows from reserves are split on a pro rata basis among all depositors, insured and uninsured.

$$\frac{\partial \hat{q}(r_L, r, \delta)}{\partial r} > 0 \Leftrightarrow u'(r) < \rho.$$

An increase in δ increases monitoring: $\frac{\partial \hat{q}}{\partial \delta} > 0$. This "charter value effect" of deposit insurance is described in Cordella, Dell'Ariccia, and Marquez (2018). Because the deposit rate is given when the banker chooses her monitoring, a higher share of insured deposits amounts to a greater implicit subsidy from the deposit insurance, thereby reducing the repayments to depositors and increasing the banker's profits. As a consequence, higher deposit insurance coverage strengthens monitoring incentives.[14]

The banker's expected profit takes the same form as before in Equation (7) except that the implicit subsidy from funding with a share δ of insured deposits is added. Substituting the average deposit rate and the optimal monitoring choice into the expected profits yields

$$\Pi = \hat{q}(r_L, r)L(r_L) + rR - (u(r)D) - \frac{\kappa \hat{q}(r_L, r)^2}{2} + S(\delta, r_L, r, R),$$

where $S(\delta, r_L, r, R) \equiv \delta(1 - \hat{q}(r_L, r, \delta))(u(r)D - rR)$ is the implicit subsidy from the deposit insurance. The subsidy is equal to the part of insured deposit funding costs that has to be covered by the deposit insurance in case of bank default. As can be seen from the expression for $S(\cdot)$, an increase in R reduces the implicit subsidy. This is because the deposit insurance can rely on a larger amount of safe assets to cover (part of) its liabilities in case the loans fail.

The transmission of monetary policy works as before through the portfolio adjustment and loan risk channels. Since optimal monitoring increases in the risk-free rate whenever the safe asset effect dominates the deposit pass-through effect, the condition for the loan risk channel to weaken monetary transmission remains formally the same as in the benchmark model with $\delta = 0$.

However, the presence of insured deposits changes the relative importance of the portfolio adjustment and loan risk channels in the transmission of monetary policy.

[14] Cordella, Dell'Ariccia, and Marquez (2018, Proposition 1) show that the charter value effect occurs if the share of deposit liabilities that are priced "at the margin" is sufficiently small. This is the case for our specification because we abstract from such deposits entirely.

Proposition 4. *Given a share δ of insured deposits, the loan risk channel dominates the portfolio adjustment channel, i.e., $\frac{dr_L^*}{dr} < 0$, if and only if*

$$\frac{\partial \hat{q}(r_L^*, r, \delta)}{\partial r} \frac{r}{\hat{q}(r_L^*, r, \delta)} > 1 + \frac{\hat{q}(r_L^*, r, \delta)\delta}{1-\delta}.$$

Comparing Propositions 2 and 4 shows that the condition for the dominance of the loan risk channel is stronger when the banker is funded with insured deposits. The reason is that the banker obtains a larger implicit subsidy from deposit insurance when she holds fewer safe assets. This asset substitution motive provides an additional incentive for the banker to increase her loan issuance when the risk-free rate falls. Thus, deposit insurance strengthens the portfolio channel and alleviates the problem of transmission reversal. Simply put, the deposit insurance subsidy mitigates the adverse effect of lower rates on the bank's profitability by increasing its profits.

Hypothesis 3. *The reversal rate $\hat{r}$ is smaller for banks that are funded with a larger share of insured deposits. In the limit for $\delta \to 1$, the reversal rate ceases to exist.*

4.2 Endogenous Deposit Choice, Deposit Shocks, and Liquidity Requirements

In this section, we briefly discuss the consequences of relaxing Assumptions 2 and 3 for our main results. In the benchmark model, the fixed amount of deposits (Assumption 2) determines the bank's balance sheet length and Assumption 3 implies that the bank holds a strictly positive amount of safe assets whose rate of return, in contrast to the loan rate, cannot be controlled by the banker. These assumptions ensure that the banker is exposed to the safe asset effect so that reductions in the risk-free rate can reduce her expected profits and lead to higher risk-taking and lesser loan issuance.

We now dispense with Assumption 2, i.e., we allow the banker to endogenously choose the amount of deposits and we consider two alternatives to Assumption 3. Under both alternatives, the banker continues to be exposed to the safe asset effect. First, we consider exogenous liquidity shocks to deposits, i.e., exogenous inflows and outflows to and from the depositors' accounts that randomly change the bank's end-of-period safe asset holdings. Second, we consider an exogenously imposed liquidity requirement, akin to the Basel regulations' liquidity coverage ratio (LCR).

It is worth pointing out that in the absence of these or other alternative assumptions, the banker in our model would have no incentives to hold safe assets. Absent the safe asset effect, the loan risk channel would always work into the same direction as the portfolio adjustment channel.

Deposit Shocks. We begin by considering a variant of the model where the bank can choose its deposits at the beginning of date 0. However, depositors are subject to a liquidity shock at the start of date 1, i.e., they face inflows and outflows to and from their deposit accounts. We assume that the bank cannot invest additional deposits in $t = 1$ into loans so that deposit flows must be balanced by an equivalent change in safe assets.[15]

To rule out precautionary motives for holding safe assets, we assume that the bank can access the central bank's standing deposit and lending facilities at an interest rate r to deposit excess reserves or to cover deposit outflows and reserve shortfalls.[16]

Furthermore, we assume that the bank can also borrow ex ante from the central bank up to a fraction $\sigma \in (0, 1)$ of its loan issuance, i.e., we impose $R \geq -\sigma L$.

Liquidity shocks, denoted x, are proportional to deposits, D, and are drawn from a continuous distribution $F(\cdot)$ and with density $f(\cdot)$ over support $[-1, z]$. zD is the maximal inflow to an individual deposit account. We assume that the liquidity shocks realize after the bank has contracted the deposit rate, set its loan rate, and has chosen the optimal monitoring effort. Without loss of generality, we set $\mathbf{E}[x] = 0$.

As before, we solve the model backwards. Given r_D, the optimal monitoring of the bank is still determined by Equation (3). The random inflows and outflows to deposit accounts affect the deposit cost

[15] Inflows to deposit accounts automatically add to the bank's central bank reserves. Outflows from deposit accounts need to be covered by running down reserves or by additional borrowing from the central bank.

[16] Allowing for a symmetric interest rate corridor around the main policy rate by making the standing borrowing rate higher than the standing deposit rate would complicate our analysis without altering the main results.

of the bank. In particular, if the bank is solvent, depositors receive r_D on their entire deposit holdings at maturity. With probability $1-q$, the bank defaults. In this case, depositors obtain a pro rata share of the remaining assets. The expected repayment to depositors must be equal to their outside option $u(r)$ such that

$$r_D = \frac{u(r) - \frac{(1-\hat{q})r\int_{-1}^{z}\max\{R+xD,0\}dF(x)}{D}}{\hat{q}}. \tag{12}$$

By substituting r_D into Equation (3), we can solve for the bank's monitoring choice $\hat{q}(r_L, D; r)$. The partial effects of r_L, r, and D on the banker's optimal monitoring $\hat{q}$ reflect the effects of these variables on her expected profits. As before, the effects of r_L and r are ambiguous, with the respective conditions now taking into account expected deposit flows.[17] However, the effect of D on $\hat{q}$ is unambiguously negative, i.e., $\frac{\partial \hat{q}}{\partial D} < 0$. This is because $u(r) \geq r$ so deposits are relatively more expensive than borrowing from the central bank (cf. Assumption 1).

LEMMA 2. *The bank chooses a strictly positive loan issuance $L^*(r)$. Given Assumption 1, the bank minimizes its funding cost by choosing $R^* = -\sigma L^*$ and $D^* = (1-\sigma)L^*$.*

Lemma 2 shows that the bank borrows from the central bank on a permanent basis as long as this is feasible (i.e., if $\sigma > 0$). Even though the bank does not hold a positive level of reserves ex ante, the possibility that it ends up with a positive reserve balance due to random deposit inflows implies that the loan risk channel can still mitigate and even dominate the portfolio channel.

PROPOSITION 5. *The loan risk channel dominates the portfolio adjustment channel, i.e., $\frac{dr_L}{dr} < 0$, if and only if*

$$\frac{\partial \hat{q}(r_L^*, r)}{\partial r}\frac{r}{q(r_L^*, r)} > 1 + \frac{\hat{q}(r_L^*, r)F\left(\frac{\sigma}{1-\sigma}\right)}{1-F\left(\frac{\sigma}{1-\sigma}\right)}. \tag{13}$$

[17] See the appendix for details.

As Proposition 5 shows, the condition for the loan risk channel to dominate the portfolio adjustment channel is similar to condition (11) when deposits are exogenous. The difference is that condition (13) depends on the probability that the bank ends up with safe asset holdings due to inflows into its depositors' accounts.

Inflows to deposits reflect the amount of safe assets that the bank cannot adjust optimally ex ante. Therefore, the probability of ending up with a positive balance can be interpreted as a measure of the ease with which the banker can adjust her safe assets. At one extreme, if the probability of an inflow of deposits becomes negligibly small, $F(\sigma/(1-\sigma)) \approx 1$, then condition (13) could never hold. In this case, the loan risk channel and the portfolio adjustment channel always go in the same direction and a reversal rate cannot exist. As is the case for a fully levered bank in Dell'Ariccia, Laeven, and Marquez (2014, Proposition 3), a lower risk-free rate leads to less risk-taking. On the contrary, if the bank would almost surely obtain a deposit inflow, i.e., $F(\sigma/(1-\sigma)) \rightarrow 0$, then condition (13) converges to our benchmark condition (11).

Condition (13) further allows us to illustrate the effect of permanent central bank lending programs on the existence of the reversal rate.

HYPOTHESIS 4. *The reversal rate becomes smaller if the central bank is willing to fund a larger share of the banker's lending, i.e.,* $\frac{\partial \hat{r}}{\partial \sigma} < 0$. *In the limit, for* $\sigma \rightarrow 1$*, the reversal rate ceases to exist.*

Consider the extreme case where the bank can finance its entire loan portfolio by borrowing from the central bank ex ante, i.e., $\lim \sigma \rightarrow 1$. In this case, a reversal rate would cease to exist.[18] This case is similar to the case with full deposit insurance, $\delta = 1$, in Section 4.1. The entire risk of the bank's loan issuance and the bank's exposure to interest rate risk would be borne by the central bank, and lower policy rates would unambiguously increase the bank's profit.[19]

[18]The right-hand side of Equation (13) converges to ∞, while the left-hand side assumes a finite value, implying that the condition could never be satisfied.

[19]We abstract from the possibility that the central bank can risk-adjust its interest rate when lending to the banker. In practice, central banks are able to

Binding Liquidity Requirement. Next, instead of Assumptions 2 and 3, we assume that the banker can endogenously choose her deposits, but she is required to hold a certain fraction of her deposits in the form of safe and liquid assets, e.g., reserves with the central bank or government bonds. This requirement is akin to the LCR that banks must satisfy under Basel III regulations (see Brunnermeier, Abadi, and Koby 2023 for a similar assumption). As we now show, under a binding liquidity requirement, the portfolio adjustment channel and the loan risk channel always move into the same direction. However, they both switch sign once the safe asset effect dominates the deposit pass-through effect. The banker's liquidity requirement can be written as

$$R \geq \rho D,$$

where ρ is now the exogenously given regulatory liquidity ratio. To the extent that $u(r) \geq r$, the liquidity requirement is binding. Since the expected profits are strictly decreasing in D, the banker minimizes the amount of deposits. Combining the liquidity requirement and the funding constraint yields

$$\frac{L}{1-\rho} = D.$$

Substitution into the banker's profits yields

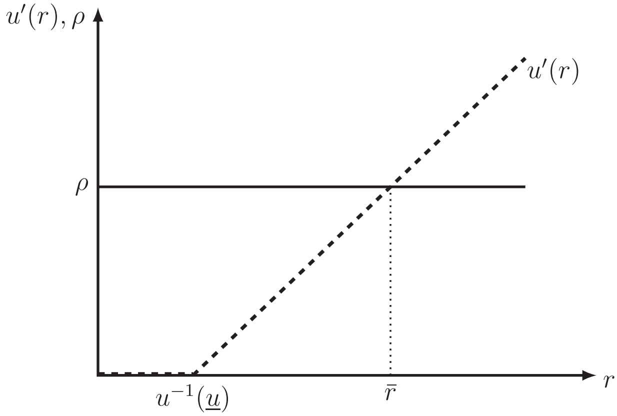
$$\Pi = q\left(r_L - \frac{r_D - \rho r}{1-\rho}\right) L(r_L) - \frac{\kappa q^2}{2}.$$

Because of the binding liquidity requirement, the direction of the portfolio adjustment channel also depends on the relationship between deposit pass-through and safe asset effect (like the loan risk channel). Thus, compared to Equation (9), the two channels are perfectly aligned, and we have

$$\frac{dr_L^*}{dr} = \underbrace{\frac{\partial r_L^*}{\partial r}}_{\text{portfolio adjustment channel}} + \underbrace{\frac{\partial r_L^*}{\partial q} \times \frac{\partial \hat{q}(r_L^*, r)}{\partial r}}_{\text{loan risk channel}} \propto \left(\frac{u'(r) - \rho}{1-\rho}\right). \tag{14}$$

achieve some degree of risk adjustment by lending against collateral and applying haircuts to riskier asset classes.

Figure 6. Reversal Rate with a Binding Liquidity Requirement



Note: For $r > \bar{r}$, the portfolio adjustment and the loan risk channel are positive, while they become negative for $r < \bar{r}$.

PROPOSITION 6. *Under a binding liquidity requirement, a reversal of monetary transmission occurs whenever the safe asset effect dominates the deposit pass-through effect. The reversal rate is*

$$\hat{r} = \bar{r}, \qquad \textit{where } \bar{r} \textit{ satisfies } u'(r) = \rho.$$

A higher liquidity requirement weakens the transmission of monetary policy.

Figure 6 illustrates the case of a binding liquidity requirement. Because ρ is now exogenously determined, the solid curve is flat at the level set by regulation. For $r < \bar{r}$, the safe asset effect dominates and reverses both the loan risk and the portfolio adjustment channel, i.e., a further reduction in the risk-free rate leads to a higher loan rate and a reduced loan issuance.

The case of a binding liquidity requirement allows us to emphasize a potential cost associated with liquidity requirements. The literature usually discusses the direct costs of liquidity requirements, i.e., the opportunity cost of foregoing profitable investments when a larger share of deposits is held in the form of more liquid but less profitable assets. Our model reveals another indirect cost of liquidity requirements, namely the costs that arise from the impairment of the monetary transmission channel. As can be seen in Equation (14), an increase in ρ reduces the effect of r on r_L^*. Moreover, once ρ is sufficiently high, monetary transmission is reverted.

4.3 Depositors' Outside Option

Finally, let us briefly discuss how the results in our model depend on Assumption 1. The crucial element of Assumption 1 is the lower bound on the outside option, whereas the additional assumptions (convexity of $u(r)$ and continuity of $u'(r)$) are technical and imposed for the sake of tractability. Consider the following example where depositors, instead of holding deposits, could either invest into a risk-free bond that pays r at date 1 or hold cash which provides a per-unit convenience yield θ and requires a per-unit storage cost ζ. Thus, $u(r) = \max\{1 + \theta - \zeta, r\}$ and $u'(r) = 1 - \mathbb{1}_{[r<1+\theta-\zeta]}$. For this specification of $u(r)$, the convexity and continuity assumptions ($u''(r) > 0$ and $\lim_{r\downarrow 1+\theta-\zeta} = 0$) fail to hold. Because $\rho \in (0, 1)$, it follows that $\rho > u'(r)$ if and only if $r < 1 + \theta - \zeta$. Since $u'(r)$ jumps discontinuously at $1 + \theta - \zeta$, the critical $\overline{r}$ at which the safe asset effect dominates the deposit pass-through effect equals the lower bound of the outside option. Hence, the safe asset effect can dominate the deposit pass-through effect for small values of r even without the continuity and convexity imposed by Assumption 1.[20]

What about the possibility that deposits themselves provide a convenience yield so that $u(r) < r$? Because the main results in the paper depend on the marginal costs and benefits of deposits versus reserve assets, allowing for a convenience yield on deposits such that $u(r) < r$ for $r > u^{-1}(\underline{u})$ would leave the results in Propositions 1–3 unaffected.[21]

[20]The continuity and convexity assumptions ensure that $\overline{r} \geq u^{-1}(\underline{u})$ and that at $r = \overline{r}$ there is no discontinuity so deposit pass-through and safe asset effect are balanced at the margin.

[21]Changing the ordering between the outside option and the risk-free rate would, however, change the implications derived in Hypothesis 1. In this case, an exogenous increase in deposits would increase the banker's expected profit and therefore increase her incentives to monitor and lead her to issue more loans. Note, however, that $u(r) < r$ would allow the bank to make a risk-free profit from

The key element in Assumption 1 is the assumption that the outside option of depositors cannot fall below $\underline{u}$. Suppose we dispense with this assumption and set $u(r) = r$ for all values of r, which is a standard assumption in the corporate finance and banking literature, e.g., Dell'Ariccia, Laeven, and Marquez (2014) and Martinez-Miera and Repullo (2017). Because $\rho \in (0, 1)$ while $u'(r) = 1$, the deposit pass-through effect dominates the safe asset effect for all values of r and a lower interest rate always leads to an increase in monitoring, $\partial\hat{q}/\partial r < 0$. This mirrors the effect of r on the bank's risk-taking incentives for the case of sufficiently high leverage in Dell'Ariccia, Laeven, and Marquez (2014, Proposition 3). As a consequence, the loan risk channel always amplifies the portfolio adjustment effect and lower interest rates unambiguously lead to a lower loan rate and higher loan issuance. This argument shows that the lower bound on the depositors' outside option is a key condition for the weakening of monetary transmission via the loan risk channel.

5. Conclusion

This paper argues that the empirically observed correlation between weaker monetary transmission and higher risk-taking in an environment of low interest rates (e.g., Miller and Wanengkirtyo 2020 or Arce et al. 2021) can be viewed as the consequence of an agency friction between banks and their depositors.

The main contributions of our paper are two. First, we show that lower policy rates lead banks to increase risk-taking when the pass-through to deposit rates is too small to compensate for the reduction in the profitability of banks' safe assets. Higher risk-taking, in turn, leads to a weakening of the monetary transmission because it induces banks to optimally raise loan rates and issue fewer loans.

Second, our model complements Brunnermeier, Abadi, and Koby (2023) by showing an alternative mechanism by which a reversal of monetary transmission can arise. The existence of a reversal

issuing deposits. To the extent that the bank could control the level of deposits (as in Section 4.2), the banker would issue as much deposits as possible.

rate depends on banks' characteristics (insured deposits, monitoring technology, leverage). Our model emphasizes that the reversal of monetary transmission is only an extreme manifestation of the more general phenomenon of weakened transmission due to higher risk-taking incentives in a low interest rate environment. This phenomenon should be of concern to central banks and may require them to devise policies that address the underlying causes of weaker transmission.

Our model suggests two policy implications that could help to alleviate the problem of weaker transmission. First, when operating in an environment with high excess reserves, central banks could implement reserve remuneration schemes that boost profits of banks holding excess reserves. While such schemes redistribute seigniorage revenues back to banks, they could nevertheless strengthen the transmission in an environment with protracted excess reserves and render monetary policy more effective. In this sense, our model provides a rationale for the two-tiered remuneration for excess reserves by the Eurosystem, which seeks to mitigate the effect of negative interest rates on bank profitability.[22]

Second, even though we abstracted from explicitly considering the effect of bank equity and capital regulation, our model can also speak to a recent debate on the importance of bank capitalization for monetary policy. In the context of our standard agency model, a capital requirement would weaken the link between loan rates and monitoring incentives. Put differently, an increase in loan risk would have a relatively smaller effect on the optimal loan rate if the bank must satisfy a larger capital requirement. As a consequence, a higher capital requirement would reduce the relative weight of the loan risk channel and strengthen monetary transmission via the portfolio adjustment channel. For banks with a smaller leverage, the reversal rate would be lower and the range of interest rates where transmission is unimpeded would be larger. Our model, therefore, echoes arguments by Gambacorta and Shin (2018) or Darracq Pariès, Kok, and Rottner (2020) who argue that bank capital matters not only for the central bank's financial stability but also for its monetary policy mandate and for the transmission of monetary policy.

[22] https://www.ecb.europa.eu/mopo/two-tier/html/index.en.html.

Appendix

A.1 Proofs

Proof of Lemma 1. Maximizing expected profits for a given deposit rate r_D with respect to q yields the first-order condition

$$r_L L - r_D D + rR - \kappa q = 0.$$

By substituting r_D from the participation constraint, we can obtain $\hat{q}$ as the solution to the following implicitly defined function:

$$\phi(q, r_L, r) \equiv r_L L - \frac{u(r)D - rR}{q} - \kappa q = 0.$$

The latter is quadratic in q. Following Allen, Carletti, and Marquez (2015), we take the larger of the two roots, such that

$$\frac{\partial \phi}{\partial q} = \frac{u(r)D - rR}{q^2} - \kappa < 0.$$

Moreover, we have

$$\frac{\partial \phi}{\partial r} = \frac{R - u'(r)D}{q}$$

and, using the fact that $R = D - L(r_L)$,

$$\frac{\partial \phi}{\partial r_L} = r_L L'(r_L) + L(r_L) - \frac{r}{q} L'(r_L).$$

An application of the implicit function theorem yields the expressions for $\partial\hat{q}/\partial r_L$ and $\partial\hat{q}/\partial r$.

Proof of Proposition 1. From Equation (7), the first-order condition for the optimal loan rate is given by

$$\begin{aligned} \frac{d\Pi}{dr_L} =\ & \hat{q}(r_L, r)\left(r_L L'(r_L) + L(r_L)\right) - rL'(r_L) \\ & + \frac{\partial \hat{q}}{\partial r_L} \underbrace{\left(r_L L(r_L) - \kappa\hat{q}\right)}_{=(u(r)D - rR)/q} = 0 \end{aligned}$$

$$= \hat{q}(r_L, r)\left(r_L L'(r_L) + L(r_L) - \frac{r}{\hat{q}(r_L, r)} L'(r_L)\right) \times \left(1 - \frac{u(r)D - rR}{u(r)D - rR - \hat{q}^2\kappa}\right) = 0.$$

$\hat{q}$ and the second bracket are positive, so that the optimal r_L^* satisfies condition (8) in the text.

The second-order condition, evaluated at the critical point r_L^*, becomes[23]

$$r_L L''(r_L^*) + 2L'(r_L^*) - \frac{r}{\hat{q}} L''(r_L^*) = -\frac{L''(r_L^*)L(r_L^*)}{L'(r_L^*)} + 2L'(r_L^*) < 0,$$

which is satisfied since $L(\cdot)$ is a decreasing and concave function. Thus, r_L^* maximizes the bank's profits.

Applying the implicit function theorem to the first-order condition evaluated at r_L^* yields

$$\frac{dr_L^*}{dr} = \frac{\partial r_L^*}{\partial r} + \frac{\partial r_L^*}{\partial q}\frac{d\hat{q}}{dr}$$
$$= -\frac{-\frac{L'(r_L^*)}{\hat{q}} + \frac{r}{\hat{q}^2} L'(r_L^*)\frac{\partial \hat{q}}{\partial r}}{-\frac{L''(r_L^*)L(r_L^*)}{L'(r_L^*)} + 2L'(r_L^*)} \gtreqless 0 \Leftrightarrow -\frac{L'(r_L^*)}{\hat{q}}\left(1 - \frac{\partial \hat{q}}{\partial r}\frac{r}{\hat{q}}\right) \gtreqless 0, \tag{A.1}$$

where we replaced $\frac{d\hat{q}}{dr}$ with $\frac{\partial \hat{q}}{\partial r}$ because $\frac{\partial \hat{q}}{\partial r_L} = 0$ when evaluated at $r_L = r_L^*$.

Equation (A.1) implies that the loan risk channel weakens the portfolio channel whenever $\partial\hat{q}/\partial r > 0$, which is equivalent to $u'(r) < \rho$ (cf. Lemma 1).

Next, we show the existence of a value $\overline{r}$ such that for all $r < \overline{r}$, we must have $u'(r) < \rho$. Note that by Assumption 3, for all $r < u^{-1}(\underline{u})$ we have $\rho = R/D = 1 - L(r_L^*(r))/D > 0 = u'(r)$. If r becomes sufficiently large, R converges to a positive and finite value, while $u'(r)$ diverges (because of the strict convexity of $u(\cdot)$ for $r > u^{-1}(\underline{u})$) so that we have $u'(r) > \rho$ for sufficiently large r. Thus, there exists a smallest value $\overline{r}$ such that $u'(\overline{r}) = \rho$. For all $r < \overline{r}$, we have $u'(r) < \rho$.

[23]Note that the partial effect of r_L on $\hat{q}$ is irrelevant for determining the sign of the second-order condition since $\partial\hat{q}/\partial r_L = 0$ when evaluated at r_L^*.

Thus, for $r < \overline{r}$, we have $u'(r) < \rho$ and, as a consequence of Lemma 1, $\partial\hat{q}/\partial r > 0$. From Equation (A.1) follows that the loan risk channel weakens the transmission via the portfolio channel for $r < \overline{r}$.

Proof of Proposition 2. The proof follows immediately from Equation (A.1):

$$\frac{dr_L^*}{dr} < 0 \;\Leftrightarrow\; 1 < \frac{\partial\hat{q}}{\partial r}\frac{r}{\hat{q}}.$$

Proof of Proposition 3. We show the existence of $\hat{r}$ that satisfies

$$1 = \frac{\partial\hat{q}(r_L^*, \hat{r})}{\partial r}\frac{\hat{r}}{\hat{q}(r_L^*, \hat{r})}.$$

From the proof of Lemma 1 it follows that

$$\frac{\partial\hat{q}}{\partial r}\frac{r}{\hat{q}} = \frac{(u'(r)D - R)r}{u(r)D - rR - \hat{q}^2\kappa} \geq 1 \;\Leftrightarrow\; (u(r) - u'(r)r)D \geq \kappa\hat{q}^2.$$

The last inequality requires that $u'(r)D \leq R$ since $u(r)D - rR < \kappa\hat{q}^2$ (cf. Lemma 1). Therefore, consider $u'(r) < \rho$. Since $u''(r) > 0$, the left-hand side of the above inequality is strictly decreasing in r. Since $u'(r) = 0$ for $r < u^{-1}(\underline{u})$, we have $\text{argmax}_r\{u(r) - u'(r)r\} = u^{-1}(\underline{u})$. Thus, a necessary and sufficient condition for the existence of a reversal rate is that κ satisfies $\kappa\hat{q}^2 \leq \underline{u}D$. Note further that

$$\frac{d\kappa\hat{q}(\kappa)^2}{d\kappa} = \frac{\hat{q}^2}{u(r)D - rR - \hat{q}^2\kappa}\left(u(r)D - rR + \kappa\hat{q}^2\right) < 0.$$

Thus, we can find a value $\underline{\kappa}$ such that $\underline{\kappa}\hat{q}(\underline{\kappa})^2 = \underline{u}D$ and where $\underline{\kappa}$ also satisfies the condition for $\partial\phi/\partial q < 0$ in the proof of Lemma 1. Since $(u(r) - u'(r)\hat{r})D - \kappa\hat{q}^2$ is strictly decreasing in r for $r \leq \overline{r}$, there exists $\hat{r} < \overline{r}$ such that for $\kappa \geq \underline{\kappa}$

$$(u(\hat{r}) - u'(\hat{r})\hat{r})D - \kappa\hat{q}^2 = 0. \tag{A.2}$$

For $r < \hat{r}$, we have

$$(u(r) - u'(r)r)D > \kappa\hat{q}^2 \;\Leftrightarrow\; \frac{\partial\hat{q}}{\partial r}\frac{r}{\hat{q}} > 1.$$

Proof of Hypothesis 1. We consider an exogenous increase in the deposit volume and show that this leads to an increase in excess reserves, a higher reserves-deposit ratio, and less lending.

The equilibrium effect of an increased D follows by applying the implicit function theorem to the two equilibrium conditions

$$r_L L(r_L) - \frac{u(r)D - r(D - L(r_L))}{q} - \kappa q = 0,$$
$$r_L L'(r_L) + L(r_L) - \frac{rL'(r_L)}{q} = 0.$$

Let J^* denote the Jacobian of the above system of two equations evaluated at the optimum. From the proofs of Lemma 1 and Proposition 1 follows that $J^* < 0$ (when the variable vector is (r_L, q)). Note further that the second equation is independent of D. Thus, by the implicit function theorem

$$\frac{dq^*}{dD} \propto -\frac{u(r) - r}{q^*} < 0 \quad \text{and} \quad \frac{dr_L^*}{dD} \propto \frac{u(r) - r}{q^*} > 0.$$

Since r_L increases in D, a higher D leads to less lending and higher excess reserves

$$\frac{dL^*}{dD} = L'(r_L^*)\frac{dr_L^*}{dD} < 0 \quad \text{and} \quad dR = dD - L'(r_L^*)\frac{dr_L^*}{dD} > 0.$$

Finally, note that the latter implies also a higher reserves-deposit ratio ρ because $\rho < 1$ and $L'(r_L^*)\frac{dr_L^*}{dD} < 0$ such that we obtain

$$\frac{d\rho}{dD} = \frac{1}{D}\left(1 - \rho - L'(r_L^*)\frac{dr_L^*}{dD}\right) > 0.$$

Proof of Hypothesis 2. Applying the implicit function theorem to Equation (A.2) yields

$$\frac{\partial \hat{r}}{\partial \kappa} = \frac{\frac{d\kappa \hat{q}^2}{d\kappa}}{-ru''(r)D - 2\kappa\hat{q}\frac{\partial \hat{q}}{\partial r}} > 0 \quad \text{and}$$

$$\frac{\partial \hat{r}}{\partial D} = \frac{-(u(r) - u'(r)r) + 2\hat{q}\kappa \frac{\partial \hat{q}}{\partial D}}{-ru''(r)D - 2\kappa\hat{q}\frac{\partial \hat{q}}{\partial r}} > 0.$$

Proof of Proposition 4. $\hat{q}$ is given by the solution to the following implicit function:

$$\phi(q, r_L, \delta, r) \equiv r_L L(r_L) - \left(\delta + \frac{1-\delta}{q}\right)(u(r)D - rR) - \kappa q = 0,$$

with

$$\frac{\partial \phi}{\partial q} = \frac{1-\delta}{q^2}(u(r)D - rR) - \kappa < 0,$$

$$\frac{\partial \phi}{\partial r} = \frac{(R - u'(r)D)(q\delta + (1-\delta))}{q^2} > 0 \Leftrightarrow \rho > u'(r),$$

$$\frac{\partial \phi}{\partial r_L} = r_L L'(r_L) + L(r_L) - \frac{\delta q + (1-\delta)}{q} r L'(r_L),$$

and

$$\frac{\partial \phi}{\partial \delta} = \frac{1-q}{q}(u(r)D - rR) > 0.$$

Given $\hat{q}$, the first-order condition for the banker's optimal loan rate is given by

$$\hat{q}\left(r_L L'(r_L) + L(r_L) - \frac{\delta q + (1-\delta}{q} r L'(r_L)\right) \times \left(1 - \frac{(\hat{q}\delta + (1-\delta))(u(r)D - rR)}{(1-\delta)(u(r)D - rR) - \kappa\hat{q}^2}\right) = 0.$$

Since the second bracket is strictly positive, the optimal loan rate satisfies

$$r_L L'(r_L) + L(r_L) - \frac{\delta q + (1-\delta)}{q} r L'(r_L) = 0.$$

Application of the implicit function theorem yields

$$\frac{dr_L^*}{dr} \propto -(1-\delta)L'(r_L)\left(1 + \frac{\delta\hat{q}}{1-\delta} - \frac{\partial \hat{q}}{\partial r}\frac{r}{\hat{q}}\right).$$

Thus, $\frac{dr_L^*}{dr} < 0$ if and only if $1 + \frac{\delta\hat{q}}{1-\delta} < \frac{\partial \hat{q}}{\partial r}\frac{r}{\hat{q}}$.

Proof of Hypothesis 3. From the proof of Proposition 4 it follows that the reversal rate $\hat{r}(\delta)$ is given by the solution to

$$\frac{\partial \hat{q}}{\partial r}\frac{r}{\hat{q}} - 1 - \frac{\delta \hat{q}}{1-\delta} = 0.$$

Using the expressions for $\partial \hat{q}/\partial r$, we can rewrite the latter as

$$u(r)D - \delta r R - (1-\delta)u'(r)rD - \kappa \hat{q}^2 = 0. \tag{A.3}$$

For $\delta = 0$, the above condition is equal to Equation (A.2), implying that $\hat{r}(\delta)$ converges to the value of the reversal rate in Proposition 3. Another application of the implicit function theorem to Equation (A.3), taking into account that for $r = \hat{r}$ we have $u'(r) < \rho$ and $\partial R/\partial r = 0$, implies $\frac{\partial \hat{r}}{\partial \delta} < 0$.

Note further that for $\delta \to 1$, Equation (A.3) cannot be satisfied since $\hat{q}$ is the larger root, which implies that $\kappa \hat{q}^2 - u(r)D + rR > 0$. Hence, for $\delta \to 1$, the reversal rate ceases to exist.

Proof of Lemma 2 and Proposition 5. The adjusted profit function becomes

$$\Pi = q\left(r_L L(r_L) + r\int_{-1}^{z} (R + x\,D)\,dF(x) - r_D D\right) - \frac{\kappa q^2}{2}.$$

Because $E[x] = 0$, we can simplify to the same profit function as in our baseline model,

$$\Pi = q\,(r_L L(r_L) + r\,R - r_D D) - \frac{\kappa q^2}{2}.$$

Inserting the participation constraint into the first-order condition for q implicitly defines the function $\hat{q}(r_L, D, r)$

$$\phi(r_L, D, r) = r_L L(r_L) + r\,R - \frac{u(r)D - (1-q)r\int_{-1}^{-\rho}(R + xD)\,dF(x)}{q} - \kappa q = 0.$$

Taking the larger of the two roots, we obtain

$$\begin{aligned}\frac{\partial\phi}{\partial r} &= qR - u^{'}D + (1-q)\int_{-\rho}^{z}(R + xD)\,dF(x)\\ &= R - (1-q)\int_{-1}^{-\rho}(R+xD)\,dF(x) - u^{'}D\end{aligned}$$

and

$$\begin{aligned}\frac{\partial\phi}{\partial r_L} &= q((r_L - r)L^{'} + L) - (1-q)rL^{'}\int_{-\rho}^{z} dF(x)\\ &= q(r_L L^{'} + L) - rL^{'} + (1-q)rL^{'}\int_{-1}^{-\rho} dF(x),\end{aligned}$$

as well as

$$\begin{aligned}\frac{\partial\phi}{\partial D} &= qr - u(r) + (1-q)r\int_{-\rho}^{z}(1+x)\,dF(x)\\ &= r - u(r) - (1-q)r\int_{-1}^{-\rho}(1+x)\,dF(x) < 0,\end{aligned}$$

which is unambiguously negative for $r \leq u(r)$.

The first-stage profit function, given the required return for the expected equilibrium monitoring choice, becomes

$$\begin{aligned}\Pi(r_L, D; r) = \hat{q}(r_L L(r_L) + r\,R) - u(r)D\\ - (1-q)r\int_{-1}^{-\rho}(R+xD)\,dF(x) - \kappa\frac{\hat{q}^2}{2}.\end{aligned}$$

Differentiating with respect to D and r_L yields the first-order conditions for a profit maximum. As the bank optimally minimizes deposit costs, we evaluate the first-order condition at $D^* = (1-\sigma)L^*(r_L)$ and $R^* = -\sigma L^*(r_L)$, such that $\rho = -\frac{\sigma}{1-\sigma}$.

Using the implicit function theorem we obtain

$$\frac{dr_L}{dr} = -\frac{\begin{array}{c}-L' + (1-\hat{q})L'\int_{-1}^{\frac{\sigma}{1-\sigma}} dF(x))\\ \quad + \left(r_L L' + L - rL'\int_{-1}^{\frac{\sigma}{1-\sigma}} dF(x)\right)\frac{\partial\hat{q}}{\partial r}\end{array}}{\frac{\partial^2\Pi}{\partial r_L^2}}.$$

For r_L^* to be the optimal loan rate in equilibrium, we must have $\frac{\partial^2\Pi}{\partial r_L^2} < 0$. Therefore, $\frac{dr_L}{dr} < 0$ if and only if the numerator is negative. Using the first-order condition $\frac{\partial\Pi}{\partial r_L} = 0$, we can simplify to

$$\frac{r}{\hat{q}}\left(1 - \int_{-1}^{\frac{\sigma}{1-\sigma}} dF(x)\right)\frac{\partial\hat{q}}{\partial r} > 1 - (1-\hat{q})\int_{-1}^{\frac{\sigma}{1-\sigma}} dF(x) \;\Leftrightarrow\; \frac{r}{\hat{q}}\frac{\partial\hat{q}}{\partial r} > \frac{1 - (1-\hat{q})\int_{-1}^{\frac{\sigma}{1-\sigma}} dF(x)}{\left(1 - \int_{-1}^{\frac{\sigma}{1-\sigma}} dF(x)\right)},$$

which corresponds to the condition in Proposition 5. Note that as $\sigma \to 1$, the left-hand side approaches zero and the right-hand side $\hat{q}$ such that the condition can never be fulfilled. If the bank can fund all loans by borrowing from the central bank, reversal rate cannot exist.

Proof of Hypothesis 4. The reversal rate $\hat{r}$ is implicitly defined by

$$\psi(\hat{r},\sigma) \equiv \frac{\hat{r}}{\hat{q}}\frac{\partial\hat{q}}{\partial r} - 1 - \hat{q}\left(\frac{F(\frac{\sigma}{1-\sigma})}{1 - F(\frac{\sigma}{1-\sigma})}\right) = 0.$$

By the implicit function theorem, $\frac{\partial\hat{r}}{\partial\sigma} = \frac{\partial\psi/\partial\sigma}{\partial\psi/\partial r} < 0$, because $\frac{F(\frac{\sigma}{1-\sigma})}{1-F(\frac{\sigma}{1-\sigma})}$ strictly increases in σ as the distribution function $F(\cdot)$, is an increasing function and at $r = \hat{r}$, we have $\partial\psi/\partial r < 0$.

Proof of Proposition 6. The banker's optimal monitoring choice is the same as in the benchmark model, i.e., $\hat{q}$ is given by the implicitly defined function $\hat{q}(r_L, r)$. Substituting $\hat{q}$ and the deposit rate into the expected profits yields

$$\Pi = \hat{q}r_L L(r_L) - \left(\frac{u(r) - \rho r}{1-\rho}\right)L(r_L) - \frac{\kappa\hat{q}^2}{2}.$$

The first-order condition determining the bank's loan issuance is given by

$$\left(\hat{q}r_L - \frac{(u(r) - \rho r)}{1-\rho}\right)L'(r_L) + \hat{q}L(r_L) + \frac{(u(r) - \rho r)L(r_L)}{\hat{q}}\frac{\partial\hat{q}}{\partial r_L} = 0.$$

Using the expression for $\partial\hat{q}/\partial r_L$ implies that the optimal loan rate r_L^* must satisfy

$$\left(r_L^* - \frac{(u(r) - \rho r)}{\hat{q}(1-\rho)}\right) L'(r_L^*) + L(r_L^*) = 0.$$

The second-order sufficient condition is satisfied when evaluated at r_L^*. Totally differentiating the first-order condition yields

$$\frac{dr_L^*}{dr} = \frac{\frac{L'(r_L)}{\hat{q}}\left(1 + \frac{(u(r)-\rho r)L(r_L)}{\hat{q}\left(\kappa - \frac{(u(r)-\rho r)L(r_L)}{\hat{q}^2}\right)}\right)}{\frac{\partial^2 \Pi}{\partial r_L^*}} \cdot \left(\frac{u'(r) - \rho}{1-\rho}\right).$$

Since the term multiplying $(u'(r) - \rho)/(1-\rho)$ is strictly positive, it follows immediately that

$$\frac{dr_L^*}{dr} \gtrless 0 \Leftrightarrow u'(r) \gtrless \rho \Leftrightarrow r \gtrless \bar{r},$$

where $\bar{r}$ solves $u(r) = \rho$.

A.2 Proportional Monitoring Cost

This section shows that the key result in Proposition 2, i.e., that

$$\frac{dr_L}{dr} < 0 \Leftrightarrow \frac{\partial\hat{q}(r_L^*, r)}{\partial r}\frac{r}{\hat{q}(r_L^*, r)} > 1$$

remains unchanged if monitoring costs are proportional to loan issuance, i.e.,

$$c(q, r_L) = \frac{\kappa}{2}q^2 L(r_L).$$

To show this, we derive the first-order condition determining the bank's optimal monitoring effort:

$$r_L L(r_L) - r_D D + r(D - L(r_L)) - cqL(r_L) = 0.$$

The optimal monitoring effort $q(r, r_L)$ is implicitly defined by the first-order condition after substituting for r_D:

$$r_L L(r_L) - cqL(r_L) - \frac{u(r)D - r(D - L(r_L))}{q} = 0.$$

Application of the implicit function theorem yields

$$\frac{\partial \hat{q}(r_L, r)}{\partial r_L} = \frac{r_L L'(r_L) + L(r_L) - \frac{r}{q} L'(r_L) - cqL'(r_L)}{cL(r_L) - \frac{u(r)D - rR}{q^2}} \gtrless 0,$$

and

$$\frac{\partial \hat{q}(r_L, r)}{\partial r} = \frac{R - u'(r)D}{cL(r_L) - \frac{u(r)D - rR}{q^2}} \gtrless 0.$$

Given $\hat{q}(r_L, r)$, the bank maximizes its profits by choosing the loan rate r_L. The profit function is given by

$$\hat{q}(r_L, r) r_L L(r_L) + r(D - L(r_L)) - u(r)D - \frac{c}{2} \hat{q}(r_L, r)^2 L(r_L).$$

Differentiating with respect to r_L yields the first-order condition that pins down r_L^*:

$$q(r_L, r) \left(r_L L'(r_L) + L(r_L) - \frac{r}{q(r_L, r)} L'(r_L) - \frac{c}{2} q(r_L, r) L'(r_L) \right) \\ + (r_L L(r_L) - cq(r_L, r) L(r_L)) \frac{\partial q(r_L, r)}{\partial r_L} = 0.$$

Dividing the latter equation by $\hat{q}$ and adding and subtracting $c\hat{q}L'/2$, we obtain

$$\left(r_L L'(r_L) + L(r_L) - \frac{r}{q(r_L, r)} L'(r_L) - cq(r_L, r) L'(r_L) \right) \\ + (r_L L(r_L) - cq(r_L, r) L(r_L)) \frac{\partial q(r_L, r)}{\partial r_L} \frac{1}{\hat{q} r_L, r)} + \frac{c}{2} q(r_L, r) L'(r_L) = 0.$$

Using the first-order condition for monitoring to replace $r_L L(r_L) - c\hat{q}$, we obtain

$$\left(r_L L'(r_L) + L(r_L) - \frac{r}{q(r_L, r)} L'(r_L) - cq(r_L, r) L'(r_L) \right) \\ + \frac{u(r)D - r(D - L(r_L))}{q(r_L, r)^2} \frac{\partial \hat{q}(r_L, r)}{\partial r_L} + \frac{c}{2} q(r_L, r) L'(r_L) = 0.$$

Substituting the expression for $\partial\hat{q}/\partial r_L$ and collecting terms, we finally obtain

$$cL(r_L)\left(r_L L'(r_L) + L(r_L) - \frac{r}{q}L'(r_L) - cq(r_l, r)L'(r_L)\right) + \frac{c}{2}q(r_L, r)L'(r_L)\left(cL(r_L) - \frac{u(r)D - r(D - L(r_L))}{q(r_L, r)^2}\right) = 0.$$

The second-order condition is strictly negative when evaluated at the critical point r_L^* that satisfies the latter equation. Thus, from the implicit function theorem follows that the sign of dr_L^*/dr is equal to the sign of the derivative of the first-order condition with respect to r, i.e., we have (for simplicity, we have dropped the arguments from functions $\hat{q}$ and L):

$$\begin{aligned}\frac{dr_L^*}{dr} &\propto -\frac{cLL'}{\hat{q}} - \frac{cL'}{2}\frac{u'(r)D - (D - L)}{\hat{q}} \\ &\quad + \left(\frac{cLL'r}{\hat{q}^2} - \frac{c^2LL'}{2} + \frac{cL'}{2}\frac{u(r)D - r(D - L)}{\hat{q}^2}\right)\frac{\partial\hat{q}}{\partial r} \\ &= -\frac{cLL'}{\hat{q}} - \frac{cL'}{2}\left(cL - \frac{u(r)D - r(D - L)}{\hat{q}^2}\right)\frac{\partial\hat{q}}{\partial r} \\ &\quad + \left(\frac{cLL'r}{\hat{q}^2} - \frac{c^2LL'}{2} + \frac{cL'}{2}\frac{u(r)D - r(D - L)}{\hat{q}^2}\right)\frac{\partial\hat{q}}{\partial r} \\ &= -\frac{c}{\hat{q}}LL'\left(1 - \frac{\partial\hat{q}}{\partial r}\frac{r}{\hat{q}}\right),\end{aligned}$$

where the second line follows from using the expression for $\frac{\partial\hat{q}}{\partial r}$ from above. Since $-cL(r_L)L'(r_L)/\hat{q}(r_L, r) > 0$, it follows that

$$\frac{dr_L^*}{dr} < 0 \Leftrightarrow \frac{\partial\hat{q}}{\partial r}\frac{r}{\hat{q}} > 1,$$

which is the same condition as in Proposition 2 where monitoring costs are independent of $L(r_L)$.

Note, while the condition for the marginal effect of r on r_L^* remains unchanged, a comparison of the respective first-order conditions shows that if the monitoring costs are proportional to loan issuance, the bank issues fewer loans (sets a higher loan rate) to reduce the monitoring costs.

A.3 Different Outside Options for Insured Depositors

In the main text, we assume that uninsured and insured depositors have the same outside option $u(r)$. Here, we show that Proposition 4 and Hypothesis 3 remain unchanged even if insured depositors have a different outside option. To this end, let $u_I I(r)$ denote the outside option of insured depositors. The outside option of the uninsured depositors remains denoted by $u(r)$.

The first-order condition for the banker's monitoring choice is given by

$$r_L(L(r_L) + rR - (\delta u^I(r) + (1-\delta)r_D)D - \kappa q = 0,$$

where r_D denotes the interest rate on uninsured debt. Substituting Equation (5) for r_D into the first-order condition yields the implicit function for $\hat{q}(r_L, r)$:

$$\begin{aligned}\phi(\hat{q}, r_L, r) \equiv\ & r_L(L(r_L)) \\ & - \frac{(\delta\hat{q}u_I I(r) + (1-\delta)u(r))D - (\hat{q} + (1-\delta)(1-\hat{q}))rR}{\hat{q}} \\ & - \kappa\hat{q} = 0.\end{aligned}$$

Again, choosing the larger root for $\hat{q}$, we have $\frac{\partial\phi}{\partial\hat{q}} \equiv \phi_{\hat{q}} < 0$ and

$$\frac{\partial\phi}{\partial r_L} \equiv \phi_{r_L} = r_L L'(r_L + L(r_L) - (\hat{q} + (1-\delta)(1-\hat{q}))\frac{r}{\hat{q}}L'(r_L).$$

Given the implicitly defined function $\hat{q}(r_L, r)$, we next turn to the banker's optimal choice of r_L. Substituting the uninsured deposit rate and $\hat{q}$ into the profit function, we obtain

$$\begin{aligned}\pi(r_L) &= \hat{q}r_L L(r_L) + (\hat{q} + (1-\hat{q})(1-\delta))rR \\ &\quad - (\delta u_I(r) + (1-\delta)u(r))D - \frac{\kappa}{2}\hat{q}^2.\end{aligned}$$

The first-order condition for r_L is given by

$$\begin{aligned}\pi'(r_L) &= \hat{q}\left(r_L L' + L - (\hat{q} + (1-\delta)(1-\hat{q}))\frac{r}{\hat{q}}L'\right) \\ &\quad + (r_L L + \delta(rR - u_I(r)D) - \kappa q)\frac{\partial\hat{q}}{\partial r_L} = 0.\end{aligned}$$

Substituting from the first-order condition for effort choice,

$$r_L L - \kappa\hat{q} = \frac{(\delta\hat{q}u_I(r) + (1-\delta)u(r))D - (\hat{q} + (1-\delta)(1-\hat{q}))rR}{\hat{q}},$$

and the expression for $\partial\hat{q}/\partial r_L$, it follows that the optimal loan rate r_L^* must solve

$$r_L L'(r_L) + L(r_L) - (\hat{q} + (1-\delta)(1-\hat{q}))\frac{r}{\hat{q}}L'(r_L) = 0.$$

As the second-order condition for a profit maximum must be negative, it follows from the implicit function theorem that

$$\begin{aligned}\frac{dr_L^*}{dr} < 0 \;\Leftrightarrow\; & -\frac{(\hat{q} + (1-\delta)(1-\hat{q}))}{\hat{q}}L'(r_L) \\ & + \left(-\frac{r}{\hat{q}}L'(r_L) + \frac{(\hat{q} + (1-\delta)(1-\hat{q}))r}{\hat{q}^2}L'(r_L)\right)\frac{\partial\hat{q}}{\partial r} < 0.\end{aligned}$$

Rewriting the latter equation yields

$$\begin{aligned}\frac{dr_L^*}{dr} < 0 \;\Leftrightarrow\; & -\frac{(1-\delta)}{\hat{q}}L'(r_L)\left(\frac{r}{\hat{q}}\frac{\partial\hat{q}}{\partial r} - \left(1 + \frac{\hat{q}\delta}{1-\delta}\right)\right) \\ < 0 \;\Leftrightarrow\; & \frac{r}{\hat{q}}\frac{\partial\hat{q}}{\partial r} > 1 + \frac{\delta\hat{q}}{1-\delta},\end{aligned}$$

which is the same condition as in Proposition 4.

However, note that while the above condition is the same as in the main text, the magnitude of the thresholds $\bar{r}$ and $\hat{r}$ changes compared to the model with identical outside options. To see this, consider the sign of

$$\frac{\partial\hat{q}}{\partial r} > 0 \;\Leftrightarrow\; \rho > \frac{\left(\delta\hat{q}\frac{u_I'(r)}{u'(r)} + (1-\delta)\right)u'(r)}{\delta\hat{q} + (1-\delta)}.$$

It follows that the relative deposit pass-through, i.e., $u_I'(r)/u'(r)$, determines whether or not the threshold rates $\bar{r}$ and $\hat{r}$ change compared to the baseline model. Whenever the interest rate pass-through to insured and uninsured depositors is the same, $u_I'(r) = u'(r)$, then $\bar{r}$ and $\hat{r}$ remain unchanged. Otherwise, if, say, $u_I'(r) < u(r)$, then the threshold $\bar{r}$ becomes larger, i.e., the range of risk-free rates where the bank's risk-taking incentives increase following a marginal increase in r.

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Switching from Cash to Cashless Payments during the COVID-19 Pandemic and Beyond*

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Using a survey of 5,504 respondents from 22 European countries, we examine preferences regarding cash and cashless payments at the point of sale (POS) during the COVID-19 crisis. Consumers favor cashless transactions when they believe that handling cash presents a higher risk of infection. Moreover, the habits they develop during periods of restrictions and lockdowns appear to further diminish their appetite for transacting in cash. Not only do these factors affect current choice of payment method, but they also influence declared future intentions to move away from cash after the pandemic is over.

JEL Codes: E41, E42, I12, I18.

1. Introduction

The highly contagious coronavirus disease 2019 (COVID-19) was declared a pandemic on March 11 (World Health Organization 2020).

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Up to the end of December 2023, it infected officially more than 774 million people and claimed almost 7 million lives (Mathieu et al. 2020). The mental, social, and economic lives of virtually everyone around the globe were affected by this health risk, profoundly changing people's habits and behaviors. In an attempt to limit the spread of the virus, governments enforced rules pertaining to social distancing and the use of face masks, advocated self-isolation, handwashing, and other types of hygienic measures. Partially due to government-imposed lockdowns, a significant reduction in people's mobility and consumption was observed, with a substitution from in-store to online shopping becoming particularly prominent (Bounie, Camara, and Galbraith 2023).

At the same time, an unprecedented outpouring of speculation about the possible link between handling physical money and COVID-19 infections has emerged (Auer, Cornelli, and Frost 2020). Research regarding this phenomenon indicated that a significant fraction of the population reduced their transactional use of cash in response to the pandemic. In its IMPACT study, the European Central Bank (2020) showed that about 40 percent of respondents in the euro area curtailed their use of cash and 38 percent of them declared that the main stimulus for their changed payment behavior was the possibility of being infected through touching banknotes. Surveys conducted by the Federal Reserve System (Kim, Kumar, and O'Brien 2020), Bank of Canada (Chen et al. 2020), and National Bank of Poland (Kotkowski, Dulinicz, and Maciejewski 2022) reached similar conclusions, noting further that some risk-averse merchants ceased to accept cash as a means of payment. Using the Dutch payment diary data, Jonker et al. (2022) shed more light on demographic and transaction-specific drivers that influence the change in payment habits due to COVID-19. Notably, the effect of the pandemic on the transactional utility of cash is manifest not only in declarations of individual respondents but also in more aggregate statistics. The studies focusing on data from retail systems, national payment schemes, or particular banks in Canada, Switzerland, Italy, and France revealed a rapid increase in the adoption of cashless payments, despite a decline in the level of general consumption (see Ardizzi, Nobili, and Rocco 2020; Bounie, Camara, and Galbraith 2023; Dahlhaus and Welte 2021; Kraenzlin, Meyer, and Nellen 2020).

In this paper, we further probe the utility of cash during the COVID-19 crisis. Using a unique data set, we can model respondents' inclination to switch from cash to cashless instruments. The richness of our data source permits us to disentangle two critical pandemic-related factors that drive underlying behaviors. Firstly, there is the direct impact of an individual's perception of viral transmission risk associated with touching banknotes and coins. Secondly, and equally importantly, this global health emergency has changed habits related to shopping, human interaction, mobility, health regimens, and ways of working. Entrenchment of these habits could have an indirect but lasting influence on payment method preferences. Our factor analysis indicated that those shifts in behavioral patterns could be categorized by whether they occurred in the physical sphere or in the cyberspace. By controlling for a wide range of respondents' and country-level characteristics, we extricated these direct and indirect influences in a logistic regression setting. We document that both fear of contagion and altered habits played a prominent role in the decision to abandon cash for transactional purposes during the COVID pandemic. Analogous results are obtained when modeling the respondents' intention to use cashless instruments more frequently after the pandemic is over. Notably, changes in habits related to physical contact exerted a more statistically and economically powerful impact on payment preferences of respondents than the altered behaviors in the online environment.

Several aspects distinguish our work from existing studies. The analysis of cash usage by the European Central Bank (2020) performed during the pandemic period reports only aggregated figures, without attempting to link COVID-19 responses to the selection of payment method at an individual level. Although Jonker et al. (2022) overcame this shortcoming by explicating changes in the payment behavior of Dutch consumers, our analysis is on a much larger scale—we examine 22 European countries rather than 1. What is more, to the best of our knowledge, this is the first study empirically linking the magnitude of fear of viral contagion with the choice of payment instrument. Similarly, the fact that changes in other habits could have a domino-like effect on peoples' payment choices has hitherto not been considered in the literature. To add further depth to our inquiry, we not only consider historical preferences towards cashless payments, but also interrogate individuals' declarations about their future payment intentions after the COVID-19 pandemic is over. Our empirical model controls for a wide range of factors, including perceptions of different payment instruments, experience of using them, stances on privacy, general technical literacy, a variety of sociodemographic factors, and country-level variables such as the number of COVID-related deaths and size of the shadow economy.

The remainder of the paper is organized as follows. Section 2 presents a literature review, which embodies two important themes. It starts by reviewing the evidence on SARS-CoV-2 survival on banknotes and coins, moving subsequently to a consideration of consumer payment behavior. Section 3 outlines our methodological approach, while Section 4 provides a description of the data set, definitions of variables, and a set of summary statistics. Our main empirical results and their interpretation are included in Section 5, and this is followed by a battery of robustness checks in Section 6. Section 7 presents reflections on the practical implications of our findings. The paper ends with concluding remarks.

2. Literature Review

2.1 Methods of Payments and Infectious Disease Transmission

Studies examining the spread of pathogens through the use of cash date back to the 1970s (see, for instance, Abrams 1972). In absence of disinfection, various types of microbes could adhere to the surface of currency, leading to the transmission of communicable diseases. A study by Vriesekoop et al. (2016) exploring bacterial survival concluded that microbial persistence is greater on paper banknotes than on polymer bills and coins. According to the estimates of Pope et al. (2002), about 94 percent of $1 bills are contaminated with pathogenic or potentially pathogenic bacteria. This statistic reaches 100 percent for currency notes in Ghana (Tagoe et al. 2009). Bills could also potentially harbor fungi and yeast (Basavarajappa, Rao, and Suresh 2005), parasites (Uneke and Ogbu 2007), and viruses (Maritz et al. 2017). The literature review conducted by Angelakis et al. (2014) concludes that banknotes retrieved from hospitals may carry antibiotic-resistant MRSA, while those from food outlets may be tainted with salmonella and E. coli.

While the existence of the monetary microbiome is well documented in the medical literature, one may wonder to what extent this message reverberated through broader society prior to the COVID-19 crisis. The reaction to the study of Gedik, Voss, and Voss (2013) epitomizes the attitudes of the bygone era. Their insightful analysis examined bacterial survival on banknotes from different countries. For their work, the authors received a satirical Ig Nobel Prize for economics in 2019. One year later, the escalating death toll from coronavirus caused a sea change in general attitudes towards this problem.

Discovery of durability of SARS-CoV-2 on surfaces (Chin et al. 2020; van Doremalen et al. 2020) posed a question as to whether the virus could be transmitted via cash. Having put a droplet of the virus on a banknote, Chin et al. (2020) observed that the note remained infectious for a period of four days. Harbourt et al. (2020) investigated the persistence of SARS-CoV-2 on U.S. banknotes produced from a blend of linen and cotton. At a temperature of 4°C, the virus was detectable for 96 hours on \$1 bills and for 72 hours on \$20 notes. Surface stability however reduced with ambient temperature, with the virus being viable for eight hours at 22°C and for four hours at 37°C. A study commissioned by the Bank of England (Caswell et al. 2020) found that the virus maintained its stability on banknotes for one hour, with its presence being dramatically reduced to about 5 percent of its initial level over the subsequent five hours. Those are very low estimates compared to those of Riddell et al. (2020), who claim that the coronavirus causing COVID-19 is still detectable on polymer and paper notes 28 days following inoculation. With regard to coins, the time to complete virus decay may depend on the metal used to mint the coin. For instance, this duration appears to be 8 hours for copper and 48 hours for stainless steel (van Doremalen et al. 2020). At the time of writing, there are still many questions as to whether cash is indeed a fomite and what exactly is the severity of the risks involved. The general public was bombarded with mixed messages in this regard. For instance, the World Health Organization has recommended that people wash their hands after coming in contact with notes and coins (Pal and Bhadada 2020). However, a recent study commissioned by the European Central Bank (ECB) showed that the risk of contracting the disease from contact with cash is very low and that cash is reasonably safe to use (Tamele et al. 2021).

The question arises as to whether the dangers posed by cash can be circumvented by switching to cashless payments. After all, SARS-CoV-2 can remain stable on plastic surfaces for seven days (Chin et al. 2020), which in itself could endanger users of payment card terminals and PIN (personal identification number) pads. However, limits on contactless payments were increased in many countries during the pandemic (Mastercard 2020), obviating the need to input a PIN code for most transactions at the point of sale. The vast majority of transactions conducted online or via mobile banking also do not require contact with potentially contaminated surfaces. Consequently, one may argue that changing one's payment habits may reduce the risk of infection.

The stance of money issuers vis-à-vis the problem of jeopardized public health proved to be somewhat confusing. Central banks differed markedly in terms of their response to information about the potential threat posed by cash. Some central banks (such as the ECB and those of the United Kingdom, Germany, Austria, Sweden, and South Africa) either stressed that the risk of SARS-CoV-2 transmission through cash is minimal compared to other frequently touched objects or refused to acknowledge the possibility of contagion altogether. But a few other nations took different approaches. For instance, central banks in the United States, China, South Korea, Kuwait, Hungary, and Poland started to quarantine and disinfect cash (Auer, Cornelli, and Frost 2020; King and Shen 2020). A regional branch of the People's Bank of China proceeded to destroy banknotes that had circulated in hospitals, wet markets, and on buses (Yeung 2020). The central banks of Georgia and India started to promote cashless payments, while, at the other end of the spectrum, monetary authorities in Canada, Portugal, and Poland appealed to retailers who stopped accepting cash to discontinue such practices. Their pleas were motivated by concerns over those who are financially excluded.

2.2 Consumer Payment Behavior

Consumer payment behavior has been a burgeoning field of research since the 1980s, starting with the seminal work of Boeschoten and Fase (1989). Nowadays, country-specific inquiries into this topic are primarily carried out by central banks. The U.S. Federal Reserve has been conducting an annual Survey of Consumer Payment Choice since 2008 (Foster, Greene, and Stavins 2020) and a Diary of Consumer Payment Choice since 2015 (Greene and Stavins 2020). In a similar vein, studies regarding Dutch payment behavior have been undertaken by De Nederlandsche Bank (DNB) since 2010 (see DNB 2020). A number of other countries, including Australia, Canada, Denmark, Sweden, Germany, Poland, and Norway, also endeavor to run similar surveys at regular intervals. Going beyond national level, the ECB performed its pan-euro-area study in 2016 (see Esselink and Hernández 2017) and 2019 (ECB 2020). Taken together, the evidence gathered reveals a pattern of steady decline in the share of retail transactions conducted using cash. In the United States this share fell from about 30 percent in 2009 to 21.5 percent in 2019 (Foster, Greene, and Stavins 2020). This downward-sloping trend is mirrored in the United Kingdom with a decline from about 80 percent in 1990 to 23 percent in 2019 (Caswell et al. 2020) and in the euro area, where the proportion of cash POS and P2P (peer-to-peer) payments decreased from 79 percent to 73 percent between 2016 and 2019 (ECB 2020).

Personal payment choice is an outcome of myriad variables, both intrinsic and extrinsic to a given individual. Internal aspects embrace perceptions of different payment instrument characteristics such as perceived speed of payment, security, ease of use, and budget control (Koulayev et al. 2016; Schuh and Stavins 2016), or stances on issues like privacy and trust (Png and Tan 2020). External influences could incorporate, for instance, socioeconomic and sociopsychological factors (Stavins 2001; van der Cruijsen and van der Horst 2019). It is worth noting that the characteristics of transactions could be also important in terms of influencing the outcome. Such characteristics encompass the transaction amount (Arango-Arango et al. 2018; Wang 2016), the possibility of paying in the way one desires (Bagnall et al. 2016; Bounie, François, and Van Hove 2017), steering mechanisms used by merchants (Arango, Hyunh, and Sabetti 2015; Stavins and Shy 2015), rewards offered by issuers of cashless payments (Bolt, Jonker, and van Renselaar 2010; Simon, Smith, and West 2010), or costs associated with the transaction (Arango-Arango et al. 2018).

Prior to the COVID-19 outbreak, there was little research investigating the link between spread of contagious disease and change in people's payment behavior. Closest to this subject is the work by Galbraith and Tkacz (2013), who used payment systems data to examine the economic impact of extreme events, like the 9/11 terrorist attacks and the SARS epidemic of March–June 2003. However, at the time, the SARS epidemic did not alter behavior significantly enough to generate detectable effects. Following the escalation of COVID-19, more research on this topic started to emerge. Apart from our study, other papers that used individual-level data include the aforementioned work of Jonker et al. (2022) and that of Saroy et al. (2022) who documented a pandemic-induced shift towards cashless payments in India. The authors argued that awareness of digital payment methods, access to different instruments, and relief welfare transfers affected the shift. Another study by Cevik (2020) reported that the spread of contagious diseases like Ebola, SARS, malaria, or yellow fever decreased the demand for physical money in the affected areas and noted that this observation may have ramifications for the current situation.

Ours is a paper that focuses specifically on how the context of the COVID-19 pandemic affected intentions to use cash. In our exploration, we distinguish two important mechanisms through which such intentions could be affected. First, individuals may exhibit varying degrees of subjective fear attributable to dealing with currency that could potentially be virally contaminated. Such fears would be a direct stimulus steering consumers towards cashless transactions, insofar as cashless transactions are perceived as a lower contagion risk. Second, there could be an indirect effect arising from the fact that the pandemic has profoundly altered our ways of life. Bound by government restrictions and by the commonsensical avoidance of jeopardy, individuals showed a stronger preference for online shopping (Bounie, Camara, and Galbraith 2023; Watanabe and Omori 2020), reduced their mobility and consumption (Bounie, Camara, and Galbraith 2023; Carvalho et al. 2021; Mínguez, Urtasun, and de Mirasierra 2020), modified their working practices (Bick, Blandin, and Mertens 2023; Brynjolfsson et al. 2020), and moved their social interactions into cyberspace (Nabity-Grover, Cheung, and Thatcher 2020). Such lifestyle transformations could have serious ramifications for personal preferences over payment methods.

A question arises as to whether these lifestyle changes have become habitual and therefore enduring. We need to bear in mind that focal attention and consciousness of choice feature prominently when an action is performed for the first time. The more an activity is repeated in a stable context, the more automatic the cognitive processes become, thereby permitting speedy action (Carden and Wood 2018; Shiffrin and Schneider 1977). Lally et al. (2010) examined changes in daily routines in order to gauge how long it would take an individual to develop a new habit. In their research, the participants' median time to reach a "plateau of automaticity" was 66 days. The duration of the pandemic has exceeded this estimate by a substantial margin, allowing sufficient time for habit formation. Arguably, the context could be also viewed as stable in the sense that the possibility of infection was ubiquitous and ever-present. However, there is a fair amount of uncertainty as to how people would behave if the context were to change. For instance, the epidemic could be eradicated through a program of mass vaccination. In response to this, some individuals may remain entrenched in the habits they acquired, while others may devote more attention to accommodating the altered landscape in their decisionmaking. Any persistence of COVID-induced habits could affect general attitudes towards using cash in the long run. Our questionnaire deliberately asks respondents which of their behavioral changes are likely to endure one year after the end of the COVID-19 pandemic.

3. Methodology

Two dependent dummy variables are considered in our modeling. They record whether respondents started to use more cashless payments due to the COVID-19 pandemic (*Cashless Switch*) and whether they declare an intention to use cashless payments more often after the pandemic is over (*Cashless Intention*). Since our data set is cross-sectional rather than longitudinal in nature, we are unable to verify whether the declared intentions materialize as an actual behavior in the future. However, extant empirical evidence indicates that, when it comes to adopting technologies, there is a high correlation between intentions and actual subsequent usage (see, for instance, Davis 1989). Perhaps more importantly, the behavioral intention is considered an antecedent and a stimulus for technology adoption in the most prominent theoretical models, such as the theory of reasoned action (Ajzen and Fishbein 1980; Fishbein and Ajzen 1975) or the technology acceptance model (Davis 1989).

Since our dependent variables measuring whether a respondent switched or intends to switch to cashless payments are binary in nature, our analysis relies on traditional logit regressions (Hosmer, Lemeshow, and Sturdivant 2013). Consequently, we estimate the probability of the act or intention to switch by employing the following empirical model:

$$P(Y^i_{jk} = 1 | H_{jk},\ E_k,\ C_{jk}) = \frac{1}{1 + e^{-(\alpha + \beta(H_{jk}) + \varphi(E_k) + \gamma(C_{jk}))}} \qquad (1)$$

Two variants ($i \in \{1, 2\}$) of the dependent variable Y^i are used in the main analysis and the robustness check section, representing either *Cashless Switch* or *Cashless Intention*. Depending on the value of i, the outcome $Y^i = 1$ indicates that the person either switched to cashless payments or wishes to do so in the future; H_{jk} is the vector that measures the characteristics, perceptions, and confidence in using technology of person j living in country k; E_k is a vector of specific characteristics of country k; while C_{jk} is our core vector of COVID-19-induced fears and changes in the behavior of person j living in country k.

Our sampling uses stratification by age, gender, and size of locality, and the survey spans 22 European countries. However, the sample size in each of the nations is not necessarily proportional to its population of Internet users. To remedy this issue methodologically, we proceed to calculate the actual proportions of Internet users for each country and, in our estimation, we weight each observation by the inverse of its probability of being sampled. In other words, the higher the weighting, the higher the observation's contribution to the residual sum of squares. Such an approach is commonly used in the literature (see, for instance, Moro et al. 2020). We note in passing that unweighted estimation results lead to identical conclusions regarding the processes being modeled.

Since the standard variance-covariance matrix is no longer appropriate, we use a sandwich (White 1980) estimator to compute it.

Robust estimation of standard errors is relied upon to deal with heteroskedasticity issues. When fitting the regressions, we take necessary precautions to avoid multicollinearity problems. This is accomplished by performing factor analysis that aggregates cognate questionnaire items into a construct. Most notably, we consider two factors representing the change in habits related to the COVID-19 epidemic, which have the potential to explain the curbed appetite for cash and transcend purely fear-based rationalization.

4. Data

Collection of the data used in this study was supported by a research grant awarded by the Polish National Science Centre and was implemented by a research agency, Interactive Research Center. The source data were obtained from consumers through a survey based on computer-assisted web interviews (CAWI), which utilized an interactive Internet questionnaire. Internet users were invited to register their interest in participating through e-mail and advertising campaigns. Those who volunteered collected points that were redeemable for prizes. Survey respondents were then selected through stratified sampling from the pool of registrants. Such a data collection approach permitted us to obtain a large sample in a relatively cost-effective manner. The interactive nature of the survey afforded us the opportunity to incorporate additional clarifications and definitions of the technical terms that could be accessed by respondents without the need to exit the webpage. CAWI also allowed participants to pause and save the answers that have already been submitted, facilitating thereby the process of consulting external information sources whenever needed.

The data collection exercise was preceded by a pilot study involving 230 respondents from 22 countries. The overriding aim of this undertaking was to verify whether respondents understand and interpret the questionnaire items correctly. Minor irregularities that were identified in the questionnaire were subsequently rectified and there was no need to conduct a second pilot study. The final sample, collected during the period spanning July to August 2020, includes 5,504 respondents from 22 European countries (Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Spain, Sweden, United Kingdom). According to Eurostat (2020), the number of Internet users in those countries accounted for 96 percent of all Internet users in the European Union in 2019.

Our survey was conducted online as, due to the pandemic, conducting face-to-face interviews would not have been possible. Since only individuals with Internet access could participate, this raises a question of whether our sample is sufficiently representative of the entire population in terms of the problem studied. To assess the gravity of this problem, we collect Eurostat data on the prevalence of Internet use in the countries of interest. The country-level statistics (presented in Appendix A) were subsequently weighted by population (taken from the World Development Indicators, WDI, database) to arrive at a sample average. The 2020 statistics indicate that proportion of individuals who used Internet in the last 12 months was 90.5 percent, while the proportion of people who have ever used it stood at 92.0 percent. Fortunately, the issue of potential nonrepresentativeness may be even less significant than these statistics would indicate for reasons elucidated in Grewenig et al. (2023). They show that although it may be possible that onliners and offliners differ in their answering behavior, once both groups are interviewed in the face-to-face mode and individuals' background/demographic characteristics are controlled for, the statistical differences between the groups evaporate. We would like to note that our regressions account for demographic factors, which is likely to reduce the size of any possible bias arising from sampling to a tolerable level.

The data collection process employed stratified random sampling, with age, gender, and size of the respondent's locality acting as stratification factors. The stratification factors of gender, age, and size of locality are also used as controls in our regressions. Another control variable employed is the attitude towards privacy, which was quantified through a questionnaire item stating: "I prefer payments for shopping to be anonymous, so that no one can see what I bought and when." The possession of a card, mobile, or wearable that could be used at the point of sale is captured by the dummy variable *Cards & Mobile.* Individuals who are lacking such items face higher costs of switching to cashless technologies, in that they may be forced to open a bank account or acquire the requisite device. We also consider eight other variables that measure the respondents' perceptions, experience, technological literacy, and habits and that are built up as constructs using principal component factor analysis (Hair et al. 2013). Each of these constructs includes many highly correlated items that cannot be modeled separately due to multicollinearity problems.

The first set of factors examines the assessment of alternative cashless payment methods, namely NFC (or near-field communication) contactless payments like Google Pay, Apple Pay, or payments with wearables (smartwatches, smartbands), and QR (quick response) code payments. Each payment method is assessed across several dimensions using a five-point Likert scale, and one factor for each of the dimensions is subsequently extracted. These factors are labeled as *Convenience of Cashless Payments*, *Safety of Cashless Payments*, *Access to Cashless Payments Technologies, Ease of Use of Cashless Technologies*, and *Control over Finance with Cashless Payments.* Familiarity with technologies was encapsulated in three additional factors. The first one, called *Literacy in Using Mobile Apps*, is based on five items assessing how confident the surveyed person is in using mobile apps for transport (e.g., Uber, Bolt, Freenow), food delivery, buying tickets on public transport, paying parking fees, and tracking fitness activity. Moreover, we measure experience in using payment technologies such as Apple Pay, Google Pay, Amazon Pay, Alipay, MoneyGram, Samsung Pay, WeChat Pay, Western Union, Revolut, cryptocurrencies, and HCE (host card emulation, or mobile contactless in a card-issuer app). Principal component analysis suggests extraction of two factors (eigenvalues of 2.91 and 1.18) that are subsequently rotated using varimax rotation. The items that load clearly in one factor measure *Experience in Using Computer Payments*, while the second factor captures *Experience in Using Mobile Payments.*

Furthermore, our questionnaire comprised a series of items pertaining to habit formation during the pandemic. These items were prefaced by a request to provide an assessment of how the respondent's life will change one year after the COVID-19 pandemic is over, as compared to the time before it started. Responses to these questions were recorded on a five-point Likert scale. The first variable measured the impact of the pest on working habits ("I will work more remotely"), while the second one was designed to capture a possible increase in online activity as a substitute for physical contact

("I will meet people online more frequently"). We also endeavored to explore a shift in traveling patterns ("I will travel less in my country" and "I will travel less abroad"), as well as dining habits ("I will eat more frequently at home"). Finally, we evaluated whether COVID-19 affected personal perception of health ("I will be more focused on my health") and shopping preferences ("I will buy more online"). Two factors with eigenvalues of 2.97 and 1.01 are extracted from these predictions of future habits. The items that load clearly on the first factor capture *Change in Habits Related to Physical Contact*, while the second one clearly gauges *Change in Online Habits*.

All of the eight above-mentioned factors created for the purpose of this study underwent a rigorous process of verification with respect to internal consistency and sampling adequacy. Statistics related to this verification are reported in Table 1. By default, each of the constructs has an eigenvalue above unity. Reassuringly, the Cronbach's alphas are consistently above the recommended threshold of 0.60. The Keiser-Meyer-Olkin test does not detect any sampling inadequacy requiring remedial action, and the proportion of variance explained by the factors appears to be satisfactory.

Moving away from factors, we explore another measure that is critical to our investigation. It intends to capture individual fear related to the possibility of contracting the disease through contact with cash. However, one needs to bear in mind that measurement must be done in relative terms. Respondents will be deterred from using cash for transitional purposes only if they perceive its infection risk to be higher than that for cashless instruments. For this reason, there was a need to include two items in the questionnaire which read "I am afraid of contracting COVID-19 due to the usage of cash in physical stores" and "I am afraid of contracting COVID-19 as a result of operations with cashless payments in physical stores." By taking the difference between the responses to these two questions, we construct a variable called *Net Fear of Cash*. Since the original items were measured on a five-point scale, the resultant net fear variable ranges from -4 to $+4$.

Finally, we utilize three variables that are measured at the country level. We include the cumulative number of COVID-19 deaths (in thousands) that occurred prior to July 2020 in order to consider the general impact that the pandemic had in a given country. Furthermore, the estimated size of the shadow economy in 2016 (as

Table 1. Characteristics of Factors Used in the Study

Factor	Eigenvalue	Cronbach's Alpha	Proportion of Variance Explained	Kaiser-Meyer-Olkin Measure
Convenience of Cashless Payments	3.6510	0.8665	0.7302	0.8751
Safety of Cashless Payments	3.9730	0.9346	0.7945	0.8897
Access to Cashless Payments Technologies	3.7631	0.9161	0.7526	0.8735
Ease of Use of Cashless Technologies	3.8451	0.9236	0.7690	0.8774
Control over Finance with Cashless Payments	4.1703	0.9495	0.8341	0.8968
Literacy in Using Mobile Apps	2.3729	0.7208	0.4746	0.7818
Experience in Using Computer Payments *Experience in Using Mobile Payments*	2.1871 1.9133	0.6027	0.3701	0.8265
Change in Habits Related to Physical Contact *Change in Online Habits*	2.9795 1.0172	0.7722	0.5710	0.8265

a percentage of GDP) was considered as an explanatory variable for cash preferences arising from tax evasion and illegal activities. These estimates were sourced from Kelmanson et al. (2019). Lastly, we create a variable measuring the number of EFT-POS terminals per 1,000 inhabitants in 2020 based on the data published by Bank for International Settlements (2022), ECB (2022), and Norges Bank (2020).[1]

Table 2 provides definitions of all the variables used in the study, while Table 3 reports the corresponding summary statistics. Evaluation of these statistics paints a picture of the individuals involved in our survey. An average respondent resided in a city with less than 100,000 inhabitants and was 47 years of age. The latter figure was influenced by the fact that people under the age of 18 were not invited to participate. Women constituted 52 percent of the sample, which is representative of the broader population in the countries of interest. On average, those who were surveyed showed a slight preference towards payment anonymity but tended to pay primarily with cards and mobiles at the point of sale. When analyzing Table 3, one needs to bear in mind that all the constructs created through factor analysis have a mean of zero and a standard deviation of one.

Importantly, 41 percent of people declared that they use cashless payments more often during the COVID-19 crisis, while 47 percent stated that they will use cashless payments more frequently after the pandemic is over. An average respondent believed that the risk of contracting the coronavirus is slightly higher for cash than the cashless alternatives. Appendix B provides more detailed data in this regard by presenting a breakdown of the key variables by country. Judging from these statistics, respondents who were most keen to switch from cash to digital payments during the pandemic resided in the United Kingdom, Belgium, Ireland, and Portugal. In those countries, people were also more likely to declare their intention to further increase the frequency of cashless payments after the pandemic has been eradicated. Such behavior could be explained by the above-average fear of virus transmission through cash as compared

[1]Since the 2020 data had two missing observations (Bulgaria and Norway), we resorted to using 2019 figures for these two countries. In our judgment, this is a sensible solution since the state of the payment infrastructure does not change rapidly on a year-to-year basis.

Table 2. Definitions of Variables

Variable	Definition
Cashless Switch	A binary variable taking the value of one for the response "Yes, I pay more often cashless (by card, smartphone, smartwatch)" to the questionnaire item "Has the coronavirus pandemic (COVID-19) affected how you pay in physical stores?". The responses "Yes, I pay more cash," "Not affected (I pay the same way as I did before pandemic," "I do not know," and "I did not make any purchases during pandemic" are coded as zero.
Cashless Intention	Dummy variable measuring respondent's agreement with the statement "After the pandemic, I will use cashless payments more often" (1 = yes, 0 = no)
Gender	Dummy variable capturing respondent's gender (1 if female, 0 otherwise)
Location Size	Response to a question regarding the size of the location (including suburbs) where the respondent lives. Responses are coded on a six-point scale: 1 – Rural area 2 – City with less than 50,000 inhabitants 3 – City between 50,000 and 100,000 inhabitants 4 – City between 100,000 and 500,000 inhabitants 5 – City between 500,000 and 1,000,000 inhabitants 6 – City over 1,000,000 inhabitants
Age	Age of the respondent
Cards & Mobile	A dummy variable measuring the possession of any card, mobile, or wearable applicable at the point of sale (1 = yes, 0 = no)
Anonymity	Degree of agreement with a statement "I prefer payments for shopping to be anonymous, so that no one can see what I bought and when" measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree)
Convenience of Cashless Payments	A factor aggregating assessments of convenience of five different cashless payment technologies (contactless (NFC) payments, Google Pay, Apple Pay, QR code payments, contactless payments with wearables)
Safety of Cashless Payments	A factor combining perceptions of safety of five different cashless payment technologies
Access to Cashless Payments Technologies	A factor aggregating assessments of how widespread five different cashless payment instruments are
Ease of Use of Cashless Technologies	A factor extracted from evaluations of how easy to use five cashless payment technologies are

(*continued*)

Table 2. (Continued)

Variable	Definition
Control over Finance with Cashless Payments	A factor constructed from an assessment of how much control over personal finance is afforded by five different cashless payment technologies
Literacy in Using Mobile Apps	A factor aggregating five items assessing how confident the surveyed person is in using mobile apps for transport (e.g., Uber, Bolt, Freenow), food delivery, buying tickets on public transport, paying parking fees, and tracking fitness activity
Experience in Using Computer Payments	First factor extracted from the items measuring respondent's experience in using payment technologies such as Apple Pay, Google Pay, Amazon Pay, Alipay, MoneyGram, Samsung Pay, WeChat Pay, Western Union, Revolut, cryptocurrencies, and HCE. The items that load clearly relate to computer-based payments.
Experience in Using Mobile Payments	Second factor extracted from the items measuring respondents' experience in using payment technologies such as Apple Pay, Google Pay, Amazon Pay, Alipay, MoneyGram, Samsung Pay, WeChat Pay, Western Union, Revolut, cryptocurrencies, and HCE. The items that load clearly relate to mobile-based payment technologies.
Change in Habits Related to Physical Contact	First factor extracted from items "I will work more remotely," "I will meet people online more frequently," "I will travel less in my country," "I will travel less abroad," " I will eat more frequently at home," and "I will be more focused on my health" after the COVID-19 crisis is over. The items that load heavily are related to physical contact.
Change in Online Habits	Second factor extracted from items "I will work more remotely," "I will meet people online more frequently," "I will travel less in my country," "I will travel less abroad," " I will eat more frequently at home," and "I will be more focused on my health" after the COVID-19 crisis is over. The items that load heavily are related to online habits.
Net Fear of Cash	A variable constructed by taking the difference in responses to two questionnaire items: "I am afraid of contracting COVID-19 due to the usage of cash in physical stores" and "I am afraid of contracting COVID-19 as a result of operations with cashless payments in physical stores."
COVID Deaths	Total number of COVID-19 deaths (in thousands) for the country in which the respondent resides
Shadow Economy	Size of the shadow economy as a percentage of GDP in the respondent's country of residence
Number of EFT-POS Terminals per Thousand People	Number of terminals provided by resident payment service providers per thousand inhabitants

Table 3. Summary Statistics

Variable	Mean	Standard Deviation	Minimum	25th Percentile	Median	75th Percentile	Maximum
Cashless Switch	0.47	0.50	0.00	0.00	0.00	1.00	1.00
Cashless Intention	0.41	0.49	0.00	0.00	0.00	1.00	1.00
Gender	0.52	0.50	0.00	0.00	1.00	1.00	1.00
Location Size	2.77	1.57	1.00	1.00	2.00	4.00	6.00
Age	47.04	16.31	18.00	33.00	47.00	62.00	100.00
Cards & Mobile	0.90	0.30	0.00	1.00	1.00	1.00	1.00
Anonymity	3.28	1.12	1.00	3.00	3.00	4.00	5.00
Convenience of Cashless Payments	0.00	1.00	–2.05	–0.45	–0.06	0.67	1.94
Safety of Cashless Payments	0.00	1.00	–2.29	–0.21	–0.02	0.80	1.88
Access to Cashless Payments Technologies	0.00	1.00	–2.37	–0.36	–0.14	0.56	2.09
Ease of Use of Cashless Technologies	0.00	1.00	–2.59	–0.45	–0.07	0.62	1.70
Control over Finance with Cashless Payments	0.00	1.00	–2.36	–0.29	–0.29	0.74	1.78
Literacy in Using Mobile Apps	0.00	1.00	–0.88	–0.88	–0.31	0.52	2.42
Experience in Using Computer Payments	0.00	1.00	–1.36	–0.20	–0.20	–0.20	9.66
Experience in Using Mobile Payments	0.00	1.00	–2.97	–0.52	–0.52	0.43	5.90
Change in Habits Related to Physical Contact	0.00	1.00	–2.93	–0.53	–0.02	0.61	2.56
Change in Online Habits	0.00	1.00	–3.64	–0.59	0.16	0.68	3.19
Net Fear of Cash	0.24	1.01	–4.00	0.00	0.00	0.00	4.00
COVID Deaths	8.49	5.18	2.47	4.99	6.25	11.48	20.98
Shadow Economy	21.98	7.18	9.60	16.70	20.30	27.80	37.80
Number of EFT-POS Terminals per Thousand People	30.35	13.97	13.18	23.01	26.79	32.99	71.11

Note: Definitions of the variables can be found in Table 1. The number of observations for each of the variables listed above is 5,504.

to cashless alternatives as well as significant shifts in habits spanning both the physical and virtual realms.

Another point of interest is the joint distribution of the two dependent variables in our study. The data reported in Appendix C reveals that the values of *Cashless Switch* and *Cashless Intention* coincide for 70.35 percent of respondents. This is unsurprising, as these variables are expected to have common covariates. When we partition our sample based on the values of the two dependent variables, we discover that significant differences in the average value of *Net Fear of Cash* emerge across different subgroups. This preliminary result indicates that the fear of infection through handling physical currency is determining payment behavior.

5. Empirical Results

Table 4 presents the results of weighted logit regressions estimating the likelihood of an immediate increase in the frequency of cashless payments in response to the COVID-19 pandemic. The first specification focuses on the fear of contagion via cash, while the second one considers the impact of changing habits. Regression (3) subsumes both these determinants as well as a full set of controls, making it the most comprehensive model amongst the considered alternatives. With respect to the key explanatory variables, our empirical findings cohere with a priori predictions. *Net Fear of Cash* is positively signed and exhibits a strong statistical significance. Clearly, individuals who believe that handling cash poses a relatively serious health hazard tend to enthusiastically embrace cashless instruments. The t-statistics associated with the variable *Change in Habits Related to Physical Contact* exceed the value of 10, making it another strong predictor of payment behavior. In other words, respondents who declared an intention to alter their routines in the physical world were ceteris paribus more likely to use cashless payment methods at the point of sale. *Change in Online Habits* appears to be a further important explanatory factor, albeit the magnitude of its coefficient and its explanatory power pales in comparison to the *Change in Habits Related to Physical Contact*. One may therefore argue that, when it comes to choices of payment technologies, habits in the physical sphere are of greater consequence than those in the virtual realm.

Table 4. Modeling the Switch to Cashless Payments during the Pandemic

	(1)	(2)	(3)
Gender	0.1764**	0.1528**	0.1597**
	(0.0762)	(0.0774)	(0.0778)
Location Size	0.0265	0.0150	0.0189
	(0.0249)	(0.0253)	(0.0255)
Age	0.0047*	0.0066**	0.0063**
	(0.0025)	(0.0026)	(0.0026)
Cards & Mobile	0.6695***	0.7438***	0.7286***
	(0.1323)	(0.1334)	(0.1336)
Anonymity	–0.0560*	–0.1230***	–0.1082***
	(0.0335)	(0.0346)	(0.0349)
Convenience of Cashless Payments	0.0079	–0.0261	–0.0210
	(0.0534)	(0.0559)	(0.0560)
Safety of Cashless Payments	0.1188**	0.1245**	0.1140*
	(0.0594)	(0.0598)	(0.0604)
Access to Cashless Payments Technologies	0.0247	–0.0431	–0.0360
	(0.0535)	(0.0547)	(0.0552)
Ease of Use of Cashless Technologies	0.1515**	0.1707***	0.1600***
	(0.0601)	(0.0616)	(0.0617)
Control over Finance with Cashless Payments	0.0107	–0.0210	–0.0244
	(0.0530)	(0.0536)	(0.0544)
Literacy in Using Mobile Apps	0.3763***	0.3655***	0.3630***
	(0.0467)	(0.0469)	(0.0472)
Experience in Using Computer Payments	0.0631*	0.0166	0.0219
	(0.0361)	(0.0369)	(0.0373)
Experience in Using Mobile Payments	0.0420	0.0172	0.0195
	(0.0442)	(0.0460)	(0.0457)
COVID Deaths	0.0245***	0.0174**	0.0183**
	(0.0072)	(0.0074)	(0.0075)
Shadow Economy	–0.0132**	–0.0192***	–0.0201***
	(0.0057)	(0.0058)	(0.0058)
Number of EFT-POS Terminals per Thousand People	0.0031	0.0002	0.0011
	(0.0025)	(0.0025)	(0.0026)
Net Fear of Cash	0.2812***		0.2431***
	(0.0389)		(0.0399)
Change in Habits Related to Physical Contact		0.4748***	0.4526***
		(0.0421)	(0.0422)
Change in Online Habits		0.0981**	0.0984**
		(0.0392)	(0.0394)
Constant	–1.0736***	–0.6432**	–0.7457**
	(0.2822)	(0.2883)	(0.2907)
Observations	5,504	5,504	5,504
chi2	343.0	391.3	429.5
p-value	0	0	0
McFadden's Pseudo R-squared	0.0885	0.108	0.117

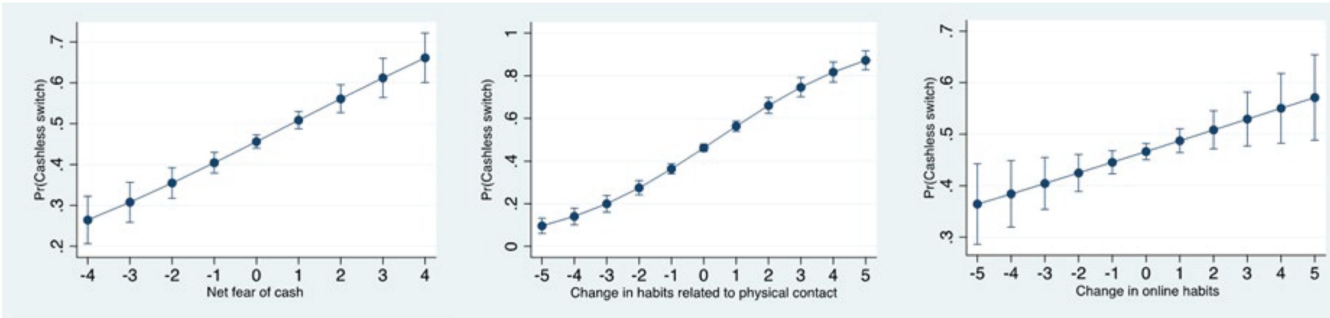
Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

While the statistical significance of fear and habits is unequivocal, the question arises as to the economic significance of our results. To probe this issue, we plot predictive functions in panel A of Figure 1. More specifically, these plots show the expected probability of *Cashless Switch* = 1 when one key independent variable is varied, and the remaining regressors are kept constant at the sample average value. When interpreting the values on the horizontal axis, one needs to remember that *Net Fear of Cash* was derived from differencing two five-point Likert scales, while a unitary move across the x-axis for the habit variables denotes a change equivalent to one standard deviation. Clearly, probabilities are increasing monotonically with all three of the variables considered in panel A, with the increase being remarkably steep for *Net Fear of Cash* and *Change in Habits Related to Physical Contact*. Judging from the plots, these two factors were decisive for many respondents in their decision to abandon cash payments at POS during the COVID-19 crisis.

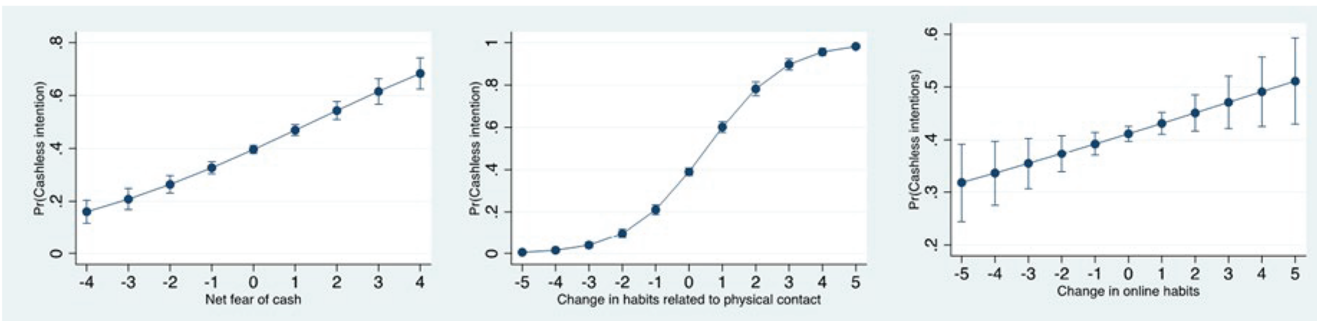
The influence of statistically significant control variables warrants further discussion. Females and those who are literate in using mobile apps showed greater proclivity to embrace cashless technologies. Unsurprisingly, those without access to cashless instruments remained dependent on banknotes and coins during the COVID crisis. Since older individuals face higher SARS-CoV-2 fatality rates (O'Driscoll et al. 2021), their health risk arising from engagement in cash-based transactions is graver. Cognizant of this reality, older people relinquished payments with physical currency more readily. Apprehension over anonymity issues and the influence of shadow economy thwarted individuals' transition towards cashless transacting. Respondents with no concerns over safety of digital payment technologies were more likely to use them frequently, which mirrors the argument of Ostlund (1974) that the perceived risk of an innovation hinders its diffusion. Furthermore, in line with the theoretical predictions of the technology acceptance model of Davis (1989), perceived ease of use of cashless instruments correlated positively with their adoption. Lastly, the number of COVID-related deaths in the respondent's country of residence was a factor contributing to the abandonment of cash. The number of deaths captures general concern over the pandemic, which goes beyond change in habits and fear of using cash captured by other variables in the model.

Figure 1. Marginal Effects for the Key Explanatory Variables

A. Estimates from the *Cashless Switch* Model



B. Estimates from the *Cashless Intention* Model



Note: The plots show a prediction of probability that either *Cashless Switch* = 1 (panel A) or *Cashless Intention* = 1 (panel B) when one of the key explanatory variables is changed, while the remaining explanatory variables are kept constant at the sample average level. The vertical bars represent 95 percent confidence intervals. The graphs in panel A are derived based on logit regression (3) in Table 4, while panel B relied on regression (3) in Table 5.

Table 5 reports weighted logit estimates for models considering the intention to use more cashless transactions after the COVID-19 pandemic is over. The results indicate that COVID-induced fear of cash may have a long memory and is likely to extend into the distant future. Once again, *Change in Habits Related to Physical Contact* exhibits stronger statistical significance and has a larger marginal effect than *Change in Online Habits* (see panel B of Figure 1). Juxtaposition of the results with those contained in Table 4 reveals that the coefficients on the fear and change in habits variables are notably larger, which coheres with our expectations. Table 4 models actual changes in behavior, while Table 5 considers reported intentions to alter behavioral patterns in the future. Since forming an intention requires less effort on the part of the respondent than taking an actual action, the parameter estimates in Table 5 are expected to be larger.

Broadly speaking, a similar pattern of significance emerges across control variables. A slight discrepancy that could be noted is the weaker explanatory power of *Age* and *Shadow Economy.* It appears that older people, who are in the highest risk group, may be reluctant to increase the frequency of their cashless payments relative to the pandemic level after the health perils have dissipated. The diminished statistical significance of the shadow economy could reflect the fact that its future size is essentially unknown and, consequently, this variable plays a smaller role in shaping intentions. The protracted pandemic is expected to have a disproportionate effect on the informal economy, where workers without formalized contracts lack job security and do not benefit from furlough schemes (Webb, McQuaid, and Rand 2020).

The economic significance of the control variables can be assessed using the average marginal effects reported in our Appendix D. What can be gleaned from these estimates is that the variable with the most pronounced economic impact is *Cards & Mobile*, regardless of whether we model the *Cashless Switch* or *Cashless Intention.* The average marginal effect for *Literacy in Using Mobile Apps* proved large for the instantaneous increase in cashless payment frequency during the pandemic but was notably attenuated in the regression considering post-pandemic payment intentions. What mattered more from the point of view of agreement with the statement "After the pandemic, I will use cashless

Table 5. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over

	(1)	(2)	(3)
Gender	0.1980**	0.1606*	0.1772**
	(0.0787)	(0.0829)	(0.0843)
Location Size	0.0256	0.0081	0.0133
	(0.0252)	(0.0270)	(0.0272)
Age	0.0023	0.0054*	0.0046
	(0.0026)	(0.0029)	(0.0029)
Cards & Mobile	0.5743***	0.7547***	0.7324***
	(0.1431)	(0.1424)	(0.1438)
Anonymity	0.0087	–0.1326***	–0.1125***
	(0.0346)	(0.0384)	(0.0391)
Convenience of Cashless Payments	0.0699	0.0233	0.0290
	(0.0554)	(0.0613)	(0.0620)
Safety of Cashless Payments	0.2486***	0.2768***	0.2715***
	(0.0629)	(0.0693)	(0.0700)
Access to Cashless Payments Technologies	0.0520	–0.0876	–0.0789
	(0.0569)	(0.0639)	(0.0651)
Ease of Use of Cashless Technologies	0.1901***	0.2330***	0.2137***
	(0.0635)	(0.0707)	(0.0717)
Control over Finance with Cashless Payments	0.1214**	0.0696	0.0714
	(0.0543)	(0.0595)	(0.0609)
Literacy in Using Mobile Apps	0.1517***	0.1288**	0.1197**
	(0.0469)	(0.0508)	(0.0514)
Experience in Using Computer Payments	0.1186***	0.0361	0.0467
	(0.0396)	(0.0410)	(0.0426)
Experience in Using Mobile Payments	0.0692	0.0314	0.0354
	(0.0458)	(0.0481)	(0.0485)
COVID Deaths	0.0284***	0.0169**	0.0187**
	(0.0074)	(0.0077)	(0.0077)
Shadow Economy	0.0105*	–0.0012	–0.0021
	(0.0059)	(0.0062)	(0.0063)
Number of EFT-POS Terminals per Thousand People	0.0005	–0.0049*	–0.0036
	(0.0025)	(0.0027)	(0.0028)
Net Fear of Cash	0.4408***		0.3955***
	(0.0438)		(0.0472)
Change in Habits Related to Physical Contact		1.0063***	0.9847***
		(0.0547)	(0.0551)
Change in Online Habits		0.1071**	0.1098**
		(0.0441)	(0.0452)
Constant	–1.8385***	–1.0840***	–1.2423***
	(0.2908)	(0.3040)	(0.3115)
Observations	5,504	5,504	5,504
chi2	395.6	537.4	550.6
p-value	0	0	0
McFadden's Pseudo R-squared	0.123	0.205	0.223

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

payments more often" was the safety of the cashless payment instruments.

6. Robustness Checks and Further Results

In order to confirm the validity of the story presented here, further tests and robustness checks were performed. To start with, we experimented with a different constellations and definitions of control variables. Firstly, the variable *Cards & Mobile* measuring the possession of any card, mobile, or wearable applicable at the point of sale was replaced with dummy variables categorizing respondents in accordance with their historical cash usage. The results displayed in Appendix E reveal a rational pattern of behavior. Individuals who made all of their transactions in cash prior to the pandemic were least likely to increase their frequency of cashless payments and showed least inclination to do so in the future. This is unsurprising, as the group includes people who operate in the shadow economy, are financially excluded, or have strong desire for anonymity. These attributes firmly anchor individuals' desire to transact in cash. For the most part, the group that was most motivated to embrace more cashless transactions comprised respondents who historically used cash in 1 percent to 30 percent of their payments. Most importantly, inclusion of the past payment behavior dummies did not change our main conclusions regarding the key explanatory variables.

Secondly, we redefined our measurements of the five attributes of cashless payments (convenience, safety, access, ease of use, and control over finance). Instead of gauging them in absolute terms, we expressed them relative to the perceived characteristics of cash. Appendix F displays our findings which, once again, reaffirm the significance of fear and habit shifts in the formation of payment preferences.

Thirdly, we interrogated the question of whether the effect of the *Age* variable is linear. To this end, we converted the continuous *Age* variable into age-group dummies, which should allow us to pinpoint the age brackets in which respondents were particularly sensitive to COVID concerns (see Appendix G). The results indicate that individuals aged between 60 and 69 were particularly eager to increase the frequency of their cashless payments during the pandemic. Perhaps this could have been attributed to the fact that

COVID mortality within this age group was higher as compared to younger people. In terms of declaring an intention to increase frequency of cashless payments after the pandemic is over, respondents between the ages of 40 to 59 were particularly reluctant to do so.

Another point of inquiry arose from the reflection that respondents who already transacted exclusively cashless in the pre-pandemic period would have the tendency to rate different aspects of such transactions highly. At the same time, they were unable to increase their frequency of cashless payments, as they already resided at the limit. A question therefore arises as to whether our results are sensitive to the exclusion of such individuals. To probe this issue further, we constructed a sample which eliminated people who did not use cash at all in the 12 months preceding the survey ($n = 363$). We rerun the logit regressions on the restricted sample (see Appendix H) and note that our main inferences regarding the three key explanatory variables remain unaltered.

In the next step of our exploration, we investigated whether there are any country-specific factors that moderate the relationship between the COVID pandemic and respondents' willingness to switch to cashless transactions. For this purpose, we created eight dummies that were subsequently interacted with the three key explanatory variables in our study (*Net Fear of Cash* and the two change-in-habits variables). These dummies indicated countries with above-median values recorded for the EFT-POS terminals per thousand people, shadow economy size, COVID deaths, power distance and uncertainty avoidance index from the Hofstede national culture database, GDP per capita expressed in purchasing power parity prices, COVID stringency index measuring the severity of government policy responses, and countries that are Scandinavian. The estimates of logistic regressions imparting these interaction terms, along with their interpretation, are shown in Appendix I.

Finally, we consider an alternative approach to modeling our dichotomous variables by employing weighted probit models. Compared to the logit regressions used in our baseline regressions, this methodological framework makes different assumptions about the error term and is based on a different link function. Reassuringly, our results from this estimation reported in Appendix J corroborate our earlier conclusions, which is a testament to the fact that our inferences are not a mere byproduct of the methodology selected.

7. Practical Considerations

The first sphere that could be affected by the collective switch to cashless transactions is the banking sector. Such shift is positively affecting the profitability of banks in at least two ways. Firstly, payment services are an enduring element embedded in the core operations of commercial banks (Rambure and Nacamuli 2008) and allow them to augment and diversify their revenue streams. Historically, banks derived most of their revenues from acting as intermediaries that take deposits and lend money, earning net interest spread in the process. However, over time, non-interest income[2] became increasingly important (DeYoung and Rice 2004). Among the non-interest revenue streams are those attributable to processing and clearing payment transactions for various parties (Radecki 1999). According to the Federal Deposit Insurance Corporation (FDIC) about 33 percent of U.S. banks' income was classed as non-interest (Li et al. 2021). McKinsey and Company (2022) report that global payments revenues totaled $2 trillion in 2019, increasing to $2.1 trillion in 2021. These figures translate into a rise in the share of banking revenues from about 39 percent to 40 percent.

Secondly, adoption of electronic payment instruments bestows additional benefits upon banks in the form of reduced operating expenses, because the cost of electronic payment equals about one-third to one-half of the paper-based equivalent (Humphrey et al. 2006). Electronic payments are subject to economies of scale, which play a significant role in the unit costs of transactions incurred by banks (Beijnen and Bolt 2009; Bolt and Humphrey 2007; Khiaonarong 2003). These bank incentives are evinced by the rise of cashless branches in which withdrawals, deposits, or check-cashing services are unavailable (Engert and Fung 2019). Emergence of such bank offices is especially conspicuous in Sweden, where about 60 percent of branches had become cashless by 2016, forcing an even greater reduction in cash usage (Engert, Fung, and Segendorf 2020).

For FinTech firms (that is, innovative, technological companies providing financial services) change of payment habits could also have profound impact. Not only do they profit from launching

[2]That is, income arising from sources unconnected to the collection of interest payments (Haubrich and Young 2019).

and operationalizing digital payment innovations, but they are also actively involved in credit markets. Ghosh, Vallee, and Zeng (2021) argue that FinTechs consider cashless payments to be a good source of verifiable information regarding the creditworthiness of a borrower, which forces the prospective loan applicants to adopt them. The customer payment data is leveraged for alternative credit underwriting models in a novel way, creating economic incentives to move away from cash.

Global consultancy firm KPMG (2020) estimates that \$361 billion was invested in FinTechs during the 2017–19 period and 58 of those companies hit a valuation of more than \$1 billion, becoming so-called unicorns (McKinsey and Company 2020a). The momentous rise of FinTechs and their impact on transforming the financial industry's landscape is undisputed (Gomber et al. 2018; Thakor 2020). Interestingly, about \$144.4 billion of the above-mentioned total investment was channeled to companies providing payment services. These companies are referred to as PayTechs and compete with banks for their non-interest revenue streams. The population of PayTechs is growing continuously, with the number of companies that obtained regulatory licenses to provide such services in the European Union soaring from 350 in 2017 to 1,475 in 2020 (Polasik et al. 2020).

Evidence also seems to point to a surge in demand for products offered by FinTech and PayTech companies during the COVID-19 crisis. According to McKinsey and Company (2020b), 6 percent of U.S. consumers opened an overall banking FinTech account during the pandemic, while Fu and Mishra (2022) report a significant rise in downloads of finance mobile apps from Google and Apple app stores during this period. Interestingly, the epidemic-induced uptick in FinTech solutions was not uniformly distributed across countries, with a number of players in the sector struggling to raise funds and balancing precariously on the edge of insolvency (see, for instance, Chernova 2019; Kelly 2020; Kodoth 2020).

Our empirical analysis could be valuable to the banking sector, as well as FinTech and PayTech firms, because it provides a clear guidance for their future marketing efforts. More specifically, it helps to identify groups that are likely to use cashless payment services more frequently in the future and pinpoint attitudes that tend to promote such behavior. Firstly, our findings indicate that women declared their willingness to increase the frequency of cashless payments more often than men. Advertising campaigns should be tailored accordingly to take full advantage of this fact. Furthermore, any promotions of digital payment instruments should endeavor to reassure the users about their safety. Our respondents attached great importance to this attribute. Similarly, ease of use of digital payment technologies proves to be a powerful stimulus for their adoption. For this reason, a deliberate effort should be undertaken to make the design of payment instruments/applications more user-friendly, without compromising their safety. Any advertising initiatives should also take account of the lasting changes in habits induced by the COVID pandemic and could perhaps attempt to reliably educate about the risk of contracting the virus via handling cash.

Another interesting result reported in this paper relates to the fact that the existence of shadow economy hindered the transition towards digital payments during the COVID-19 period, although this relationship was weaker for the reported future intentions. Vigorous actions of tax authorities and law enforcement agencies aimed at curbing the underground economic activities could potentially foster a more rapid move towards a cashless society. For many years, the shadow economy was perceived to be closely linked to cash transactions (Gordon 1990). Similarly, reduction in cash payments could have a discouraging effect on tax evasion and criminal activities. Zhang et al. (2019) find that an increase in the use of cashless payments helps to shrink and transform the shadow economy, while Schneider (2019) estimates that complete elimination of cash would decrease its size by 20.1 percent. With respect to tax compliance, two studies focusing on Greece and the euro area by Hondroyiannis and Papaoikonomou (2017, 2020) showed that that an increase in the share of card payments in private consumption led to a corresponding growth in VAT (value-added tax) revenues. For Greece, a 1 percentage point rise in this share was estimated to augment the VAT receipts by somewhere between 1 percent (Hondroyiannis and Papaoikonomou 2017) and 1.4 percent (Danchev, Gatopoulos, and Vettas 2020). Studies exploring this issue from the perspective of the whole European Union (most notably Immordino and Russo 2018 and Madzharova 2020) cohere with the conclusion that cashless payments tend to reduce VAT tax evasion.

Changes in how people pay are also critical for central banks, as these institutions are sole issuers of money and play a key role in its distribution. As shown in Subsection 2.2, the share of cash payments in retail transactions has decreased worldwide and transactional use of cash plunged even further during the COVID-19 epidemic. This, however, was eclipsed by precautionary hoarding of cash, which led to an increase in the overall demand for money (see, for instance, Caswell et al. 2020; Chen et al. 2020; Goodhart and Ashworth 2020; Kotkowski 2023). Whatever the demand, central banks need to be ready to provide an adequate supply of physical money at all times, in addition to performing their role as monetary authorities and safeguarding the financial system (Restoy 2020). This issuing obligation is especially important during times of distress, such as the COVID-19 pandemic, because failure to meet the surge in demand could heighten reputational risk. Additionally, central banks must be aware that the elevated demand would not last forever, and that they may be forced to withdraw and redeem some of the cash that is currently in circulation (Snellman, Vesala, and Humphrey 2001).

8. Conclusions

The coronavirus epidemic instilled a widespread sense of apprehension and changed the trajectories of our lives. In this paper, we examined how the disease outbreak affected consumer choices regarding payment methods at the point of sale. The results clearly indicate that those who believed that cash poses a relatively high risk of viral transmission opted for cashless alternatives. Payment behavior was also indirectly transmuted through the impact that the pandemic had on the patterns of our daily activities. Especially, our altered habitual conduct in physical spaces exerted a powerful influence, steering individuals towards cashless transactions. The drift away from physical currency was also attributable to changes in online behavior, albeit to a lesser degree. Interestingly, the possibility of contagion through cash and transformed habits not only drove the contemporaneous switch between the payment instruments but also imprinted themselves on respondents' future intentions to transact in a cashless manner, even after the COVID pandemic has been contained.

Our findings have several practical implications relevant to every link in the chain of payment transaction processing. Banks, acquirers, FinTechs, and payment organizations must be aware that COVID-like events can drastically change the volume and value of processed transactions. While in some cases it may bring a much-needed revenue stream, it also puts a strain on available resources. Failure to meet the surge in demand could heighten reputational risk. Similarly, merchants need to show flexibility in times perturbed by fear of disease contagion and dynamically evolving consumer habits. Preferred payment options should be offered to paying patrons to alleviate their anxiety. Furthermore, central banks should carry out further studies on the epidemiological safety of different payment instruments, so conclusive knowledge about this phenomenon could emerge and potentially ease angst within the population. Finally, the COVID-induced speedy move towards digital payments has the potential to disadvantage those who are financially excluded, particularly immigrants, elderly, unemployed, or disabled people. This area of concern warrants further scientific inquiry in the future.

Appendix A

Table A.1. Internet Use in Our Sample Countries in 2020

	Individuals Who Used Internet in the Last 12 Months (in %)	Individuals Who Have Ever Used the Internet (in %)	Population
Austria	89	92	8,917,205
Belgium	92	94	11,555,997
Bulgaria	74	79	6,934,015
Czech Republic	89	92	10,698,896
Denmark	99	99	5,831,404
Finland	97	98	5,530,719
France*	91	93	67,391,582
Germany	95	96	83,240,525
Greece	79	80	10,715,549
Hungary	86	88	9,749,763
Ireland	92	94	4,994,724
Italy	81	84	59,554,023
Lithuania	84	86	2,794,700
Netherlands	95	96	17,441,139
Norway	98	99	5,379,475
Poland	85	87	37,950,802
Portugal	79	82	10,305,564
Romania	85	86	19,286,123
Slovak Republic	91	93	5,458,827
Spain	93	94	47,351,567
Sweden	97	98	10,353,442
United Kingdom	98	98	67,215,293
Population-Weighted Average	90.5035	92.0413	

*Due to the lack of data, we use 2019 statistics for France.
Note: Internet use data are sourced from Eurostat, while the population data come from WDI. Survey consists of all individuals aged 16 to 74. On an optional basis, some countries collect separate data on other age groups: individuals aged 15 years or less, aged 75 or more.

Appendix B

Table B.1. Country-Level Averages for the Key Variables

	Cashless Switch	***Cashless Intention***	***Net Fear of Cash***	***Change in Habits Related to Physical Contact***	***Change in Online Habits***
Austria	0.39	0.28	0.06	–0.24	–0.14
Belgium	0.63	0.48	0.32	0.01	0.08
Bulgaria	0.29	0.34	0.28	0.17	0.01
Czech Republic	0.43	0.35	0.25	–0.15	–0.02
Denmark	0.42	0.34	0.41	–0.18	–0.10
Finland	0.41	0.38	0.16	–0.13	–0.01
France	0.42	0.37	0.14	–0.05	0.01
Germany	0.34	0.31	0.09	–0.22	–0.21
Greece	0.47	0.33	0.03	–0.18	0.12
Hungary	0.34	0.39	0.37	–0.10	–0.21
Ireland	0.63	0.51	0.35	0.20	0.06
Italy	0.40	0.38	0.10	0.23	–0.05
Lithuania	0.31	0.39	0.22	–0.08	0.01
Netherlands	0.56	0.38	0.18	–0.10	0.14
Norway	0.47	0.38	0.11	–0.22	–0.07
Poland	0.56	0.53	0.44	0.09	0.07
Portugal	0.61	0.57	0.31	0.35	0.07
Romania	0.55	0.55	0.39	0.43	0.00
Slovakia	0.39	0.33	0.23	–0.15	0.08
Spain	0.49	0.48	0.04	0.23	0.03
Sweden	0.32	0.29	0.20	–0.24	–0.07
United Kingdom	0.65	0.53	0.30	0.17	0.14

Appendix C. Exploring the Data

To investigate the issue of overlap in respondents' answers, we present in Table C.1 the data on joint distribution of the two dependent variables used in our study.

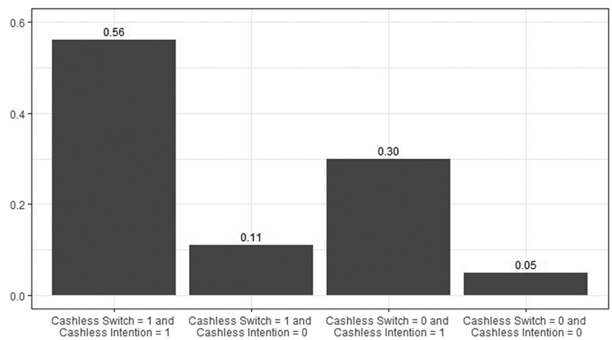
We have also examined whether the summary statistics for each of the four cohorts defined by the cells in the table above are comparable and have discovered the most pronounced differences occur for the variable *Net Fear of Cash*. Figure C.1 plots these values. This

Table C.1. Joint Distribution of the Two Dependent Variables

	Cashless Intention = 0	*Cashless Intention* = 1	Total
Cashless Switch = 0	41.12% (2,263)	12.17% (670)	53.29% (2,933)
Cashless Switch = 1	17.48% (962)	29.23% (1,609)	46.71% (2,571)
Total	58.59% (3,225)	41.41% (2,279)	100.00% (5,504)

Note: This table presents the joint distribution of *Cashless Switch* and *Cashless Intention.* The numbers presented show the proportion of the sample and the number of observations falling within a particular category in parentheses.

Figure C.1. Average *Net Fear of Cash* in Different Cohorts



Note: This figure presents averages for the variable *Net Fear of Cash* in four groups defined by their values of *Cashless Switch* and *Cashless Intention.*

discovery aligns well with the story that is being told in our paper, namely that the fear of COVID transmission through cash drives the payment choices of respondents.

Appendix D

Table D.1. Average Marginal Effects for Control Variables

	Table 4 Column 3	Table 5 Column 4
Gender	0.0376	0.0387
Location Size	0.0051	0.0044
Age	0.0011	0.0007
Cards & Mobile	0.1521	0.1259
Anonymity	–0.0160	–0.0034
Convenience of Cashless Payments	0.0005	0.0125
Safety of Cashless Payments	0.0293	0.0549
Access to Cashless Payments Technologies	0.0043	0.0089
Ease of Use of Cashless Technologies	0.0365	0.0440
Control over Finance with Cashless Technologies	0.0041	0.0267
Literacy in Using Mobile Apps	0.0850	0.0346
Experience in Using Computer Payments	0.133	0.0236
Experience in Using Mobile Payments	0.0091	0.0141
COVID Deaths	0.0053	0.0056
Shadow Economy	–0.0026	0.0025
Number of EFT-POS Terminals per Thousand People	0.0005	–0.0002

Note: This table reports average marginal effects for the control variables in logit regressions presented in Table 4 (column 3) and Table 5 (column 3).

Appendix E. Examining the Importance of Historical Cash Usage

In this appendix we attempt to assess the importance of historical cash usage in determining *Cashless Switch* and *Cashless Intention*. Our questionnaire allows us to measure the past use of cash (and by implication cashless instruments), as it includes an item phrased as follows:

Table E.1. Dummy Variables

Variables		No. of Cases
CASH_0	0% of the Payments Made by Cash	363
CASH_30	From 1% to 30% of the Payments Made by Cash	2,901
CASH_60	From 31% to 60% of the Payments Made by Cash	1,217
CASH_99	From 61% to 99% of the Payments Made by Cash	575
CASH_100	100% of the Payments Made by Cash	448

What was the share of individual payment methods in your purchases in physical stores and service outlets in the last 12 months?

[Please specify the shares in the number of transactions, not the value. The selected answers should add up to approximately 100%.]

From the responses recorded, we were able to obtain data on intensity of cash utilization, which was divided into five brackets. These were later transformed into dummy variables, as shown in Table E.1.

Subsequently, these dummies were entered into our logit regressions, while simultaneously excluding the *Cards & Mobile* dummy in order to alleviate any multicollinearity concerns. In a similar vein, one of the dummies (CASH_99) is omitted to circumvent the perfect multicollinearity problem. The results are presented in Tables E.2 and E.3.

Table E.2. Modeling the Switch to Cashless Payments during the Pandemic (including past payment behavior)

	(1)	(2)	(3)
Gender	0.1655**	0.1415*	0.1477*
	(0.0775)	(0.0787)	(0.0790)
Location Size	0.0357	0.0257	0.0284
	(0.0250)	(0.0255)	(0.0257)
Age	0.0039	0.0056**	0.0053**
	(0.0026)	(0.0027)	(0.0027)
Anonymity	–0.0226	–0.0920***	–0.0808**
	(0.0339)	(0.0351)	(0.0352)

(*continued*)

Table E.2. (Continued)

	(1)	(2)	(3)
Convenience of Cashless Payments	–0.0116	–0.0404	–0.0371
	(0.0543)	(0.0565)	(0.0566)
Safety of Cashless Payments	0.0875	0.0891	0.0816
	(0.0608)	(0.0614)	(0.0622)
Access to Cashless Payments Technologies	0.0250	–0.0393	–0.0323
	(0.0536)	(0.0555)	(0.0557)
Ease of Use of Cashless Technologies	0.1551**	0.1739***	0.1650***
	(0.0614)	(0.0626)	(0.0629)
Control over Finance with Cashless Payments	0.0061	–0.0301	–0.0329
	(0.0547)	(0.0553)	(0.0561)
Literacy in Using Mobile Apps	0.3421***	0.3313***	0.3312***
	(0.0479)	(0.0480)	(0.0483)
Experience in Using Computer Payments	0.0755**	0.0333	0.0374
	(0.0373)	(0.0378)	(0.0380)
Experience in Using Mobile Payments	0.0216	0.0004	0.0041
	(0.0453)	(0.0471)	(0.0466)
COVID Deaths	0.0211***	0.0145*	0.0154**
	(0.0073)	(0.0076)	(0.0076)
Shadow Economy	–0.0097*	–0.0154***	–0.0165***
	(0.0059)	(0.0059)	(0.0060)
Number of EFT-POS Terminals per Thousand People	0.0030	0.0004	0.0012
	(0.0025)	(0.0026)	(0.0026)
Net Fear of Cash	0.2615***		0.2232***
	(0.0391)		(0.0398)
Change in Habits Related to Physical Contact		0.4739***	0.4533***
		(0.0428)	(0.0429)
Change in Online Habits		0.0736*	0.0753*
		(0.0400)	(0.0401)
CASH_0	0.6380***	0.5973***	0.5477***
	(0.1903)	(0.1898)	(0.1938)
CASH_30	1.0890***	1.0979***	1.0739***
	(0.1337)	(0.1361)	(0.1370)
CASH_60	0.8344***	0.8203***	0.8308***
	(0.1420)	(0.1453)	(0.1463)
CASH_100	–0.1690	–0.2671	–0.2335
	(0.1891)	(0.1907)	(0.1920)
Constant	–1.3766***	–0.8782***	–0.9617***
	(0.2892)	(0.2980)	(0.2993)
Observations	5,504	5,504	5,504
chi2	415.1	446.6	477.4
p-value	0	0	0
McFadden's Pseudo R-squared	0.109	0.129	0.136

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table E.3. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (including past payment behavior)

	(1)	**(2)**	**(3)**
Gender	0.1780**	0.1435*	0.1578*
	(0.0804)	(0.0849)	(0.0860)
Location Size	0.0322	0.0163	0.0196
	(0.0253)	(0.0273)	(0.0276)
Age	0.0012	0.0039	0.0032
	(0.0027)	(0.0030)	(0.0030)
Anonymity	0.0544	–0.0916**	–0.0770*
	(0.0356)	(0.0395)	(0.0400)
Convenience of Cashless Payments	0.0501	0.0092	0.0129
	(0.0569)	(0.0623)	(0.0631)
Safety of Cashless Payments	0.2231***	0.2458***	0.2436***
	(0.0634)	(0.0699)	(0.0706)
Access to Cashless Payments Technologies	0.0469	–0.0849	–0.0759
	(0.0563)	(0.0652)	(0.0661)
Ease of Use of Cashless Technologies	0.1948***	0.2416***	0.2252***
	(0.0654)	(0.0725)	(0.0740)
Control over Finance with Cashless Payments	0.1198**	0.0545	0.0569
	(0.0565)	(0.0614)	(0.0631)
Literacy in Using Mobile Apps	0.1072**	0.0807	0.0740
	(0.0485)	(0.0524)	(0.0532)
Experience in Using Computer Payments	0.1193***	0.0432	0.0507
	(0.0401)	(0.0423)	(0.0432)
Experience in Using Mobile Payments	0.0293	–0.0063	–0.0005
	(0.0468)	(0.0498)	(0.0499)
COVID Deaths	0.0260***	0.0152*	0.0169**
	(0.0074)	(0.0078)	(0.0078)
Shadow Economy	0.0171***	0.0064	0.0052
	(0.0061)	(0.0065)	(0.0065)
Number of EFT-POS Terminals per Thousand People	0.0005	–0.0047*	–0.0034
	(0.0027)	(0.0028)	(0.0029)
Net Fear of Cash	0.4185***		0.3702***
	(0.0439)		(0.0473)
Change in Habits Related to Physical Contact		1.0197***	0.9985***
		(0.0552)	(0.0557)
Change in Online Habits		0.0772*	0.0800*
		(0.0449)	(0.0460)
CASH_0	1.1021***	1.1036***	1.0491***
	(0.2043)	(0.2210)	(0.2283)
CASH_30	1.2600***	1.3722***	1.3461***
	(0.1492)	(0.1553)	(0.1587)
CASH_60	0.7843***	0.7808***	0.7989***
	(0.1574)	(0.1645)	(0.1676)

(*continued*)

Table E.3. (Continued)

	(1)	(2)	(3)
CASH_100	0.1125	–0.0596	–0.0039
	(0.2048)	(0.2100)	(0.2132)
Constant	–2.4349***	–1.5902***	–1.7295***
	(0.3086)	(0.3249)	(0.3299)
Observations	5,504	5,504	5,504
chi2	503.1	630.1	642.3
p-value	0	0	0
McFadden's Pseudo R-squared	0.146	0.230	0.245

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Appendix F. Measuring Cashless Payments Attributes Relative to Cash

In the main body of our paper, we have quantified different aspects of cashless payments (convenience, safety, access, ease of use, and control over finance) using factor analysis. This is because we needed to aggregate information on a multitude of payment technologies. The resultant variables were absolute measures, in the sense that they pertained to the cashless technologies alone.

In this appendix we produce regressions where these characteristics are expressed in relative terms. In other words, the attributes of cashless instruments were compared to those of cash. A critical issue that needs to be elucidated here is the procedure that was followed to construct these relative measures. It can be broken into two distinct steps:

(i) For any given payment characteristic (e.g., convenience or safety), we calculate the score differences between each of the six payment instruments (payment cards; HCE payments; Google Pay, Apple Pay, QR, wearables) and cash.

(ii) Factor analysis is then deployed to aggregate the score differences across all payment instruments.

In the regressions that follow (Tables F.1 and F.2), we add the word "Net" in front of a payment characteristic to highlight the fact that it has been calculated relative to cash.

Table F.1. Modeling the Switch to Cashless Payments during the Pandemic (net constructs)

	(1)	(2)	(3)
Gender	0.1776**	0.1483*	0.1558**
	(0.0765)	(0.0776)	(0.0779)
Location Size	0.0287	0.0184	0.0215
	(0.0250)	(0.0255)	(0.0256)
Age	0.0060**	0.0070***	0.0067**
	(0.0025)	(0.0026)	(0.0026)

(*continued*)

Table F.1. (Continued)

	(1)	**(2)**	**(3)**
Cards & Mobile	0.6598***	0.7166***	0.7073***
	(0.1310)	(0.1330)	(0.1330)
Anonymity	–0.0174	–0.0943***	–0.0824**
	(0.0341)	(0.0352)	(0.0353)
Net Convenience of Cashless Payments	–0.1688***	–0.1895***	–0.1678***
	(0.0512)	(0.0522)	(0.0527)
Net Safety of Cashless Payments	0.1660***	0.1401**	0.1375**
	(0.0534)	(0.0544)	(0.0549)
Net Access to Cashless Payments Technologies	–0.0117	–0.0935*	–0.0736
	(0.0503)	(0.0506)	(0.0514)
Net Ease of Use of Cashless Technologies	0.0511	0.0448	0.0332
	(0.0565)	(0.0574)	(0.0578)
Net Control over Finance with Cashless Payments	0.0136	–0.0047	–0.0051
	(0.0475)	(0.0484)	(0.0487)
Literacy in Using Mobile Apps	0.3682***	0.3556***	0.3548***
	(0.0468)	(0.0470)	(0.0473)
Experience in Using Computer Payments	0.0688*	0.0249	0.0282
	(0.0357)	(0.0365)	(0.0369)
Experience in Using Mobile Payments	0.0486	0.0204	0.0231
	(0.0438)	(0.0454)	(0.0452)
COVID Deaths	0.0203***	0.0139*	0.0150**
	(0.0072)	(0.0074)	(0.0074)
Shadow Economy	–0.0156***	–0.0229***	–0.0233***
	(0.0058)	(0.0059)	(0.0059)
Number of EFT-POS Terminals per Thousand People	0.0033	0.0008	0.0016
	(0.0025)	(0.0026)	(0.0026)
Net Fear of Cash	0.2708***		0.2308***
	(0.0391)		(0.0399)
Change in Habits Related to Physical Contact		0.4739***	0.4520***
		(0.0421)	(0.0422)
Change in Online Habits		0.0711*	0.0723*
		(0.0397)	(0.0398)
Constant	–1.1584***	–0.6335**	–0.7352**
	(0.2834)	(0.2891)	(0.2913)
Observations	5,504	5,504	5,504
chi2	357.5	406.0	440.7
p-value	0	0	0
McFadden's Pseudo R-squared	0.093	0.112	0.120

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table F.2. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (net constructs)

	(1)	(2)	(3)
Gender	0.1922**	0.1496*	0.1639*
	(0.0789)	(0.0833)	(0.0844)
Location Size	0.0299	0.0116	0.0162
	(0.0252)	(0.0271)	(0.0272)
Age	0.0038	0.0054*	0.0047
	(0.0027)	(0.0028)	(0.0029)
Cards & Mobile	0.5695***	0.7256***	0.7111***
	(0.1411)	(0.1425)	(0.1427)
Anonymity	0.0727**	–0.0902**	–0.0739*
	(0.0353)	(0.0390)	(0.0393)
Net Convenience of Cashless Payments	–0.3054	–0.3796	–0.3457
	(0.0516)	(0.0585)	(0.0589)
Net Safety of Cashless Payments	0.1512***	0.1051*	0.1066*
	(0.0556)	(0.0604)	(0.0615)
Net Access to Cashless Payments Technologies	–0.0147	–0.1826	–0.1505
	(0.0519)	(0.0562)	(0.0570)
Net Ease of Use of Cashless Technologies	0.1127*	0.1090*	0.0899
	(0.0582)	(0.0635)	(0.0646)
Net Control over Finance with Cashless Payments	0.1176**	0.0937*	0.0985*
	(0.0482)	(0.0544)	(0.0546)
Literacy in Using Mobile Apps	0.1468***	0.1207**	0.1148**
	(0.0478)	(0.0511)	(0.0516)
Experience in Using Computer Payments	0.1442***	0.0639	0.0711*
	(0.0402)	(0.0408)	(0.0426)
Experience in Using Mobile Payments	0.1088**	0.0628	0.0680
	(0.0461)	(0.0473)	(0.0478)
COVID Deaths	0.0223***	0.0113	0.0133*
	(0.0074)	(0.0077)	(0.0078)
Shadow Economy	0.0076	–0.0068	–0.0071
	(0.0059)	(0.0063)	(0.0063)
Number of EFT-POS Terminals per Thousand People	0.0010	–0.0042	–0.0030
	(0.0026)	(0.0028)	(0.0028)
Net Fear of Cash	0.4267***		0.3741***
	(0.0438)		(0.0478)
Change in Habits Related to Physical Contact		1.0339***	1.0110***
		(0.0555)	(0.0559)
Change in Online Habits		0.0736*	0.0759*
		(0.0444)	(0.0453)
Constant	–1.9791***	–1.0295***	–1.1886***
	(0.2908)	(0.3041)	(0.3094)
Observations	5,504	5,504	5,504
chi2	412.0	544.3	553.6
p-value	0	0	0
McFadden's Pseudo R-squared	0.119	0.207	0.223

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Appendix G

Table G.1. Modeling the Switch to Cashless Payments during the Pandemic (age brackets)

	(1)	(2)	(3)
Gender	0.1722**	0.1488*	0.1548**
	(0.0762)	(0.0773)	(0.0778)
Location Size	0.0247	0.0139	0.0175
	(0.0249)	(0.0253)	(0.0255)
Age < 30	–0.0830	–0.1504	–0.1187
	(0.1649)	(0.1686)	(0.1692)
Age >= 30 and < 40	–0.0949	–0.2115	–0.1697
	(0.1653)	(0.1686)	(0.1696)
Age >= 40 and < 50	0.0953	0.0413	0.0744
	(0.1589)	(0.1624)	(0.1625)
Age >= 50 and < 60	–0.0289	–0.0275	–0.0141
	(0.1604)	(0.1622)	(0.1634)
Age >= 60 and < 70	0.2033	0.0070***	0.0067**
	(0.1547)	(0.0026)	(0.0026)
Cards & Mobile	0.6639***	0.7404***	0.7244***
	(0.1324)	(0.1339)	(0.1340)
Anonymity	–0.0563*	–0.1240***	–0.1094***
	(0.0337)	(0.0348)	(0.0351)
Convenience of Cashless Payments	0.0067	–0.0258	–0.0215
	(0.0537)	(0.0562)	(0.0564)
Safety of Cashless Payments	0.1214**	0.1257**	0.1158*
	(0.0595)	(0.0601)	(0.0607)
Access to Cashless Payments Technologies	0.0228	–0.0447	–0.0376
	(0.0535)	(0.0547)	(0.0552)
Ease of Use of Cashless Technologies	0.1514**	0.1698***	0.1592***
	(0.0600)	(0.0616)	(0.0616)
Control over Finance with Cashless Payments	0.0135	–0.0176	–0.0209
	(0.0529)	(0.0538)	(0.0544)
Literacy in Using Mobile Apps	0.3771***	0.3660***	0.3639***
	(0.0466)	(0.0469)	(0.0472)
Experience in Using Computer Payments	0.0652*	0.0200	0.0253
	(0.0360)	(0.0369)	(0.0372)
Experience in Using Mobile Payments	0.0444	0.0209	0.0230
	(0.0442)	(0.0460)	(0.0458)
COVID Deaths	0.0241***	0.0170**	0.0178**
	(0.0072)	(0.0075)	(0.0075)
Shadow Economy	–0.0139**	–0.0199***	–0.0209***
	(0.0057)	(0.0058)	(0.0059)
Number of EFT-POS Terminals per Thousand People	0.0032	0.0003	0.0013
	(0.0025)	(0.0026)	(0.0026)
Net Fear of Cash	0.2844***		0.2459***
	(0.0390)		(0.0398)
Change in Habits Related to Physical Contact		0.4777***	0.4554***
		(0.0420)	(0.0421)

(*continued*)

Table G.1. (Continued)

	(1)	(2)	(3)
Change in Online Habits		0.0952**	0.0951**
		(0.0394)	(0.0395)
Constant	–0.8453***	–0.2807	–0.4228
	(0.2801)	(0.2852)	(0.2870)
Observations	5,504	5,504	5,504
chi2	350.5	401.6	440.6
p-value	0	0	0
McFadden's Pseudo R-squared	0.0895	0.110	0.118

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. In these models, the dummy for individuals aged 70 and over is excluded and, consequently, this group acts as a benchmark. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table G.2. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (age brackets)

	(1)	(2)	(3)
Gender	0.1973**	0.1593*	0.1745**
	(0.0788)	(0.0829)	(0.0843)
Location Size	0.0222	0.0056	0.0103
	(0.0253)	(0.0271)	(0.0273)
Age < 30	–0.1573	–0.2533	–0.1952
	(0.1663)	(0.1794)	(0.1813)
Age >= 30 and < 40	–0.0453	–0.2357	–0.1645
	(0.1622)	(0.1748)	(0.1751)
Age >= 40 and < 50	–0.2829*	–0.3789**	–0.3258*
	(0.1604)	(0.1712)	(0.1720)
Age >= 50 and < 60	–0.3640**	–0.3714**	–0.3543**
	(0.1621)	(0.1732)	(0.1750)
Age >= 60 and < 70	0.0076	–0.0150	0.0387
	(0.1549)	(0.1651)	(0.1668)
Cards & Mobile	0.5699***	0.7454***	0.7224***
	(0.1433)	(0.1430)	(0.1442)
Anonymity	0.0127	–0.1285***	–0.1084***
	(0.0348)	(0.0386)	(0.0393)

(*continued*)

Table G.2. (Continued)

	(1)	**(2)**	**(3)**
Convenience of Cashless Payments	0.0701	0.0264	0.0304
	(0.0555)	(0.0615)	(0.0621)
Safety of Cashless Payments	0.2607***	0.2839***	0.2805***
	(0.0633)	(0.0696)	(0.0705)
Access to Cashless Payments Technologies	0.0518	–0.0873	–0.0788
	(0.0571)	(0.0639)	(0.0652)
Ease of Use of Cashless Technologies	0.1919***	0.2355***	0.2165***
	(0.0636)	(0.0707)	(0.0718)
Control over Finance with Cashless Payments	0.1103**	0.0590	0.0598
	(0.0545)	(0.0599)	(0.0615)
Literacy in Using Mobile Apps	0.1522***	0.1263**	0.1177**
	(0.0470)	(0.0511)	(0.0517)
Experience in Using Computer Payments	0.1134***	0.0325	0.0427
	(0.0392)	(0.0408)	(0.0423)
Experience in Using Mobile Payments	0.0615	0.0270	0.0297
	(0.0460)	(0.0480)	(0.0485)
COVID Deaths	0.0286***	0.0172**	0.0190**
	(0.0074)	(0.0077)	(0.0078)
Shadow Economy	0.0105*	–0.0012	–0.0022
	(0.0059)	(0.0062)	(0.0063)
Number of EFT-POS Terminals per Thousand People	0.0006	–0.0048*	–0.0034
	(0.0026)	(0.0028)	(0.0028)
Net Fear of Cash	0.4448***		0.3981***
	(0.0435)		(0.0469)
Change in Habits Related to Physical Contact		1.0052***	0.9827***
		(0.0547)	(0.0551)
Change in Online Habits		0.1127**	0.1150**
		(0.0445)	(0.0456)
Constant	–1.5871***	–0.6104**	–0.8494***
	(0.2807)	(0.2987)	(0.3026)
Observations	5,504	5,504	5,504
chi2	407.0	534.6	552.7
p-value	0	0	0
McFadden's Pseudo R-squared	0.125	0.206	0.225

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. In these models, the dummy for individuals aged 70 and over is excluded and, consequently, this group acts as a benchmark. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Appendix H

Table H.1. Modeling the Switch to Cashless Payments during the Pandemic (cash users only)

	(1)	(2)	(3)
Gender	0.1543*	0.1290	0.1361*
	(0.0787)	(0.0797)	(0.0802)
Location Size	0.0217	0.0099	0.0150
	(0.0257)	(0.0262)	(0.0263)
Age	0.0041	0.0061**	0.0056**
	(0.0026)	(0.0027)	(0.0027)
Cards & Mobile	0.6548***	0.7256***	0.7133***
	(0.1359)	(0.1367)	(0.1370)
Anonymity	–0.0832**	–0.1440***	–0.1301***
	(0.0349)	(0.0358)	(0.0361)
Convenience of Cashless Payments	0.0052	–0.0295	–0.0231
	(0.0552)	(0.0576)	(0.0578)
Safety of Cashless Payments	0.0803	0.0953	0.0773
	(0.0618)	(0.0628)	(0.0631)
Access to Cashless Payments Technologies	0.0286	–0.0338	–0.0287
	(0.0554)	(0.0566)	(0.0570)
Ease of Use of Cashless Technologies	0.1697***	0.1865***	0.1780***
	(0.0626)	(0.0640)	(0.0641)
Control over Finance with Cashless Payments	0.0215	–0.0125	–0.0136
	(0.0552)	(0.0560)	(0.0567)
Literacy in Using Mobile Apps	0.3890***	0.3802***	0.3763***
	(0.0489)	(0.0490)	(0.0493)
Experience in Using Computer Payments	0.0469	–0.0013	0.0029
	(0.0369)	(0.0372)	(0.0377)
Experience in Using Mobile Payments	0.0371	0.0133	0.0156
	(0.0452)	(0.0466)	(0.0465)
COVID Deaths	0.0258***	0.0191**	0.0198***
	(0.0073)	(0.0076)	(0.0076)
Shadow Economy	–0.0131**	–0.0191***	–0.0200***
	(0.0058)	(0.0059)	(0.0060)
Number of EFT-POS Terminals per Thousand People	0.0024	–0.0004	0.0006
	(0.0025)	(0.0026)	(0.0026)
Net Fear of Cash	0.2936***		0.2605***
	(0.0408)		(0.0419)
Change in Habits Related to Physical Contact		0.4597***	0.4385***
		(0.0437)	(0.0438)
Change in Online Habits		0.0959**	0.0980**
		(0.0404)	(0.0406)
Constant	–0.9015***	–0.4926*	–0.5932**
	(0.2915)	(0.2969)	(0.2995)
Observations	5,141	5,141	5,141
chi2	323.1	362.8	398.1
p-value	0	0	0
McFadden's Pseudo R-squared	0.089	0.106	0.115

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table H.2. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (cash users only)

	(1)	(2)	(3)
Gender	0.1886**	0.1461*	0.1627*
	(0.0814)	(0.0860)	(0.0873)
Location Size	0.0212	0.0028	0.0089
	(0.0263)	(0.0281)	(0.0285)
Age	0.0026	0.0059**	0.0050
	(0.0027)	(0.0030)	(0.0030)
Cards & Mobile	0.5979***	0.7745***	0.7606***
	(0.1477)	(0.1442)	(0.1459)
Anonymity	–0.0159	–0.1526***	–0.1351***
	(0.0360)	(0.0397)	(0.0404)
Convenience of Cashless Payments	0.0629	0.0128	0.0198
	(0.0578)	(0.0638)	(0.0647)
Safety of Cashless Payments	0.2651***	0.3123***	0.2968***
	(0.0666)	(0.0732)	(0.0741)
Access to Cashless Payments Technologies	0.0757	–0.0550	–0.0488
	(0.0591)	(0.0666)	(0.0682)
Ease of Use of Cashless Technologies	0.2033***	0.2441***	0.2294***
	(0.0663)	(0.0736)	(0.0750)
Control over Finance with Cashless Payments	0.1091*	0.0468	0.0524
	(0.0569)	(0.0621)	(0.0641)
Literacy in Using Mobile Apps	0.1412***	0.1168**	0.1053**
	(0.0489)	(0.0530)	(0.0536)
Experience in Using Computer Payments	0.1101***	0.0204	0.0287
	(0.0404)	(0.0416)	(0.0436)
Experience in Using Mobile Payments	0.0668	0.0326	0.0358
	(0.0472)	(0.0494)	(0.0500)
COVID Deaths	0.0279***	0.0166**	0.0181**
	(0.0075)	(0.0079)	(0.0079)
Shadow Economy	0.0087	–0.0037	–0.0046
	(0.0061)	(0.0064)	(0.0065)
Number of EFT-POS Terminals per Thousand People	0.0008	–0.0046	–0.0031
	(0.0026)	(0.0028)	(0.0028)
Net Fear of Cash	0.4474***		0.4104***
	(0.0460)		(0.0492)
Change in Habits Related to Physical Contact		1.0185***	1.0005***
		(0.0570)	(0.0577)
Change in Online Habits		0.1126**	0.1181**
		(0.0458)	(0.0473)
Constant	–1.7559***	–1.0091***	–1.1621***
	(0.3007)	(0.3152)	(0.3202)
Observations	5,141	5,141	5,141
chi2	382.7	531.8	539.0
p-value	0	0	0
McFadden's Pseudo R-squared	0.125	0.208	0.227

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Appendix I. Moderating Effects

In this appendix we investigate whether interaction models could inform us about country-level factors that moderate the relationship between the COVID pandemic and the willingness to switch to cashless payments. Eight different variables are considered as possible moderating factors, which are subsequently interacted in our logistic regressions with *Net Fear of Cash* and the two changes in habits variables. To ease the task of interpretation and alleviate multicollinearity concerns, these eight variables are constructed as dummies that partition our sample into two groups—one in which a given characteristic exists or is prominent (i.e., records an above-median value) and one in which it is not. Three binary indicators were constructed from variables already used in our main analysis, namely *COVID Deaths, Shadow Economy*, and *Number of EFT-POS Terminals per Thousand People*, whereas two additional dummies derive from country scores for power distance and uncertainty avoidance index retrieved from the Hofstede national culture data set. Another two dichotomous variables split the sample into Scandinavian and non-Scandinavian countries, as well as developed versus emerging economies based on the value of GDP per capita in 2020 measured at purchasing power parity prices. The GDP data were sourced from the World Development Indicators database maintained by the World Bank. Finally, we split the countries according to their COVID stringency index, which measures the severity of policy responses to COVID-19 pandemic and was compiled by Mathieu et al. (2020). The values of the stringency index were averaged during the July to August 2020 period, which covers the timeframe when the survey was conducted. Table I.1 catalogues and describes the interaction dummies.

Table I.2 presents logit regressions with interaction terms that model the decision to pay cashless more often during the COVID pandemic.

As there are as many as 24 interaction terms across the eight regressions in the table above, we restrict ourselves to analyzing only those that are statistically significant at the 5 percent level or better. Firstly, the interaction between the Scandinavian country dummy and *Net Fear of Cash* bears a negative coefficient and proves meaningful to the choice of cashless payments during the COVID

Table I.1. Definitions of Variables

Variable	Definition
D_Scand	A dummy variable taking a value of one if the respondent resides in a Scandinavian country and zero otherwise
D_Deaths	A dummy variable taking a value of one if the respondent is from a country with an above-median number of COVID-19 deaths and zero otherwise
D_Shadow	A dummy variable taking a value of one if the respondent's country has an above-median size of the shadow economy (as a percentage of GDP) and zero otherwise
D_Stringency	A dummy variable taking a value of one if the respondent resides in a country with an above-median value of the COVID stringency index and zero otherwise
D_Developed	A dummy variable taking a value of one if the respondent inhabits a country with an above-median value of GDP per capita in international dollars in 2020 and zero otherwise
D_PD	A dummy variable taking a value of one if the respondent is from a country with an above-median value of Hofstede power distance indicator and zero otherwise
D_UA	A dummy variable taking a value of one if the respondent is from a country with an above-median value of Hofstede uncertainty avoidance index and zero otherwise
D_Terminals	A dummy variable taking a value of one if the respondent's country has an above-median number of EFT-POS terminals per thousand people and zero otherwise

epidemic. As is shown in Appendix B, respondents in all of the Scandinavian countries in our sample (Denmark, Finland, Norway, Sweden) showed below-average tendency to change their habits in response to infection risk. Similarly, many of them failed to act out their fears through switching from cash to payment instruments offering a lower risk of virus transmission. Scandinavia had already been characterized by a very high level of electronic payments prior to the COVID outbreak (Armelius, Claussen, and Reslow 2022; Engert, Fung, and Segendorf 2020), which limited the scope of further abandonment of physical currency for transactional purposes. Secondly, the impact of changes in habits in the physical space is lessened for countries with high values of the COVID stringency index. In such countries, changes in behavior may have been primarily driven by the regulations rather than the free will of respondents. Switch to cashless payments, which is entirely voluntary in

Table I.2. Modeling the Switch to Cashless Payments during the Pandemic (including interaction terms)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender	0.1616**	0.1627**	0.1536**	0.1642**	0.1585**	0.1636**	0.1563**	0.1558**
	(0.0779)	(0.0779)	(0.0778)	(0.0779)	(0.0779)	(0.0779)	(0.0779)	(0.0778)
Location Size	0.0189	0.0194	0.0185	0.0200	0.0202	0.0193	0.0185	0.0190
	(0.0255)	(0.0255)	(0.0255)	(0.0254)	(0.0255)	(0.0254)	(0.0255)	(0.0256)
Age	0.0063**	0.0063**	0.0063**	0.0062**	0.0062**	0.0061**	0.0063**	0.0065**
	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)
Cards & Mobile	0.7320***	0.7251***	0.7337***	0.7256***	0.7240***	0.7295***	0.7311***	0.7360***
	(0.1337)	(0.1332)	(0.1338)	(0.1332)	(0.1337)	(0.1332)	(0.1340)	(0.1338)
Anonymity	–0.1082***	–0.1066***	–0.1084***	–0.1061***	–0.1084***	–0.1068***	–0.1100***	–0.1060***
	(0.0349)	(0.0348)	(0.0348)	(0.0348)	(0.0349)	(0.0348)	(0.0349)	(0.0348)
Convenience of Cashless Payments	–0.0214	–0.0218	–0.0236	–0.0198	–0.0246	–0.0197	–0.0236	–0.0244
	(0.0560)	(0.0560)	(0.0560)	(0.0559)	(0.0561)	(0.0559)	(0.0560)	(0.0560)
Safety of Cashless Payments	0.1133*	0.1174*	0.1152*	0.1190**	0.1135*	0.1205**	0.1115*	0.1155*
	(0.0605)	(0.0605)	(0.0605)	(0.0607)	(0.0605)	(0.0609)	(0.0604)	(0.0607)
Access to Cashless Payments Technologies	–0.0348	–0.0374	–0.0362	–0.0358	–0.0364	–0.0377	–0.0302	–0.0356
	(0.0553)	(0.0551)	(0.0551)	(0.0551)	(0.0552)	(0.0551)	(0.0553)	(0.0551)
Ease of Use of Cashless Technologies	0.1581**	0.1587**	0.1560**	0.1572**	0.1616***	0.1573**	0.1602***	0.1529**
	(0.0618)	(0.0618)	(0.0618)	(0.0618)	(0.0618)	(0.0618)	(0.0618)	(0.0617)
Control over Finance with Cashless Payments	–0.0247	–0.0219	–0.0213	–0.0208	–0.0244	–0.0204	–0.0254	–0.0201
	(0.0544)	(0.0544)	(0.0544)	(0.0544)	(0.0545)	(0.0544)	(0.0546)	(0.0545)
Literacy in Using Mobile Apps	0.3641***	0.3624***	0.3635***	0.3639***	0.3637***	0.3632***	0.3638***	0.3641***
	(0.0473)	(0.0473)	(0.0472)	(0.0474)	(0.0472)	(0.0474)	(0.0471)	(0.0472)
Experience in Using Computer Payments	0.0219	0.0195	0.0206	0.0206	0.0231	0.0224	0.0201	0.0213
	(0.0373)	(0.0372)	(0.0373)	(0.0373)	(0.0373)	(0.0372)	(0.0373)	(0.0371)
Experience in Using Mobile Payments	0.0185	0.0198	0.0164	0.0196	0.0181	0.0192	0.0189	0.0207
	(0.0458)	(0.0459)	(0.0459)	(0.0460)	(0.0460)	(0.0460)	(0.0457)	(0.0459)
COVID Deaths	0.0180**	0.0191**	0.0181**	0.0181**	0.0191**	0.0176**	0.0186**	0.0169**
	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0076)	(0.0075)	(0.0075)
Shadow Economy	–0.0202***	–0.0201***	–0.0195***	–0.0202***	–0.0210***	–0.0217***	–0.0201***	–0.0203***
	(0.0059)	(0.0058)	(0.0060)	(0.0058)	(0.0059)	(0.0060)	(0.0060)	(0.0059)

(*continued*)

Table I.2. (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of EFT-POS Terminals per Thousand People	0.0011	0.0012	0.0012	0.0014	0.0012	0.0019	0.0013	0.0022
	(0.0026)	(0.0026)	(0.0026)	(0.0025)	(0.0026)	(0.0026)	(0.0026)	(0.0025)
Net Fear of Cash	0.2598***	0.2740***	0.2389***	0.2252***	0.2179***	0.2343***	0.1837**	0.2554***
	(0.0430)	(0.0466)	(0.0500)	(0.0521)	(0.0437)	(0.0567)	(0.0759)	(0.0428)
Change in Habits Related to Physical Contact	0.4489***	0.4283***	0.4889***	0.5459***	0.4407***	0.3894***	0.5221***	0.4971***
	(0.0441)	(0.0498)	(0.0531)	(0.0580)	(0.0454)	(0.0600)	(0.0922)	(0.0464)
Change in Online Habits	0.0977**	0.0798*	0.0745	0.1323**	0.1022**	0.0389*	0.1471*	0.0952**
	(0.0414)	(0.0457)	(0.0474)	(0.0549)	(0.0424)	(0.0337)	(0.0814)	(0.0423)
Net Fear of Cash × D_Scand	−0.2067**							
	(0.0857)							
Change in Habits Related to Physical Contact × D_Scand	0.0604							
	(0.1037)							
Change in Online Habits × D_Scand	−0.0017							
	(0.0849)							
Net Fear of Cash × D_Deaths		−0.1187						
		(0.0892)						
Change in Habits Related to Physical Contact × D_Deaths		0.0777						
		(0.0903)						
Change in Online Habits × D_Deaths		0.0626						
		(0.0816)						
Net Fear of Cash × D_Shadow			0.0230					
			(0.0780)					
Change in Habits Related to Physical Contact × D_Shadow			−0.1201					
			(0.0826)					
Change in Online Habits × D_Shadow			0.0953					
			(0.0758)					
Net Fear of Cash × D_Stringency				0.0343				
				(0.0749)				
Change in Habits Related to Physical Contact × *D_Stringency*				−0.1584**				
				(0.0805)				
Change in Online Habits × D_Stringency				−0.0609				
				(0.0735)				
Net Fear of Cash × D_Developed					0.2248***			
					(0.0726)			
Change in Habits Related to Physical Contact × D_Developed					0.1565*			
					(0.0840)			
Change in Online Habits × D_Developed					−0.0293			
					(0.0740)			
Net Fear of Cash × D_PD						0.0247		
						(0.0762)		

(*continued*)

Table I.2. (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in Habits Related to Physical Contact × D_PD						0.1432*		
						(0.0816)		
Change in Online Habits × D_PD						0.1311*		
						(0.0739)		
Net Fear of Cash × D_UA							0.0838	
							(0.0884)	
Change in Habits Related to Physical Contact × D_UA							–0.0903	
							(0.1028)	
Change in Online Habits × D_UA							–0.0616	
							(0.0904)	
Net Fear of Cash × D_Terminals								–0.0869
								(0.1200)
Change in Habits Related to Physical Contact × D_Terminals								–0.2770***
								(0.1075)
Change in Online Habits × D_Terminals								0.0239
								(0.1062)
Constant	–0.7413**	–0.7634***	–0.7542***	–0.7552***	–0.7347**	–0.7368**	–0.7486**	–0.7822***
	(0.2911)	(0.2902)	(0.2917)	(0.2903)	(0.2908)	(0.2917)	(0.2917)	(0.2911)
Observations	5,504	5,504	5,504	5,504	5,504	5,504	5,504	5,504
chi2	445.9	431.3	434.2	446.5	514.9	448.2	434.8	430.6
p	0	0	0	0	0	0	0	0
r2_p	0.117	0.117	0.117	0.118	0.118	0.118	0.117	0.118

Note: This table reports egression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2 and in Table I.1. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

nature, did not seem to keep up with the regulation-induced behavioral shifts. Thirdly, the variable *Net Fear of Cash* exerted a more prominent impact on decision to abandon cash in countries with high GDP per capita. This is unsurprising since the volume of transactions is expected to be higher for respondents from affluent nations. As more cash transactions are made, the risks are swiftly compounding, and the desire to drift away from cash becomes stronger. This, in turn, explains the statistical significance of the interaction variable. Lastly, the impact of *Change in Habits Related to Physical Contact* on the decision to switch to digital payments is weaker in countries with a large number of EFT-POS terminals per capita.

Table I.3 presents models which include interactive terms and in which the intention to increase the frequency of cashless payments after the pandemic is over acts as a dependent variable.

Two of the interactions in Table I.3 appear to be significant at the 5 percent level. Firstly, the impact of changes in habits in the physical sphere on the declared future intention is stronger in societies with a high power distance. Power distance, as the degree to which hierarchical order is accepted within society, could affect trust in institutions and, consequently, in cashless technologies. If a person feels no resistance towards power distance and is prepared to change their physical habits, transition towards cashless payments will loom large on their agenda due to the relatively high trust in financial institutions. Such rationalization is consistent with the observed positive coefficient on the interaction term. Secondly, the societal uncertainty avoidance also appears to magnify the impact of *Change in Habits Related to Physical Contact* on the future intention to transact more cashless. This means that respondents who were willing to change their physical behavior in response to the dangers posed by COVID and resided in uncertainty-averse nations were particularly eager to abandon cash for transactional purposes.

Table I.3. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (including interaction terms)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender	0.1768**	0.1821**	0.1772**	0.1820**	0.1765**	0.1856**	0.1809**	0.1729**
	(0.0843)	(0.0842)	(0.0843)	(0.0842)	(0.0844)	(0.0842)	(0.0844)	(0.0842)
Location Size	0.0133	0.0131	0.0134	0.0138	0.0133	0.0131	0.0136	0.0129
	(0.0272)	(0.0272)	(0.0273)	(0.0272)	(0.0273)	(0.0272)	(0.0272)	(0.0273)
Age	0.0046	0.0047	0.0048	0.0046	0.0047	0.0045	0.0044	0.0047
	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)
Cards & Mobile	0.7325***	0.7322***	0.7336***	0.7257***	0.7298***	0.7340***	0.7398***	0.7378***
	(0.1440)	(0.1440)	(0.1440)	(0.1436)	(0.1439)	(0.1440)	(0.1452)	(0.1443)
Anonymity	–0.1124***	–0.1094***	–0.1127***	–0.1107***	–0.1132***	–0.1085***	–0.1108***	–0.1113***
	(0.0391)	(0.0390)	(0.00391)	(0.0391)	(0.0391)	(0.0391)	(0.0391)	(0.0389)
Convenience of Cashless Payments	0.0290	0.0297	0.0272	0.0311	0.0269	0.0335	0.0346	0.0260
	(0.0620)	(0.0622)	(0.0620)	(0.0621)	(0.0621)	(0.0621)	(0.0622)	(0.0620)
Safety of Cashless Payments	0.2709***	0.2758***	0.2725***	0.2743***	0.2716***	0.2747***	0.2715***	0.2730***
	(0.0700)	(0.0701)	(0.0702)	(0.0699)	(0.0701)	(0.0701)	(0.0695)	(0.0701)
Access to Cashless Payments Technologies	–0.0788	–0.0777	–0.0778	–0.0757	–0.0795	–0.0768	–0.0776	–0.0785
	(0.0652)	(0.0650)	(0.0651)	(0.0650)	(0.0652)	(0.0650)	(0.0653)	(0.0651)
Ease of Use of Cashless Technologies	0.2135***	0.2118***	0.2122***	0.2127***	0.2144***	0.2121***	0.2166***	0.2085***
	(0.0718)	(0.0719)	(0.0718)	(0.0717)	(0.0718)	(0.0717)	(0.0718)	(0.0716)
Control over Finance with Cashless Payments	0.0711	0.0768	0.0712	0.0740	0.0715	0.0761	0.0682	0.0739
	(0.0609)	(0.0608)	(0.0608)	(0.0607)	(0.0609)	(0.0607)	(0.0606)	(0.0608)
Literacy in Using Mobile Apps	0.1197**	0.1197**	0.1194**	0.1210**	0.1196**	0.1209**	0.1166**	0.1202**
	(0.0515)	(0.0516)	(0.0514)	(0.0516)	(0.0514)	(0.0516)	(0.0513)	(0.0515)
Experience in Using Computer Payments	0.0469	0.0440	0.0463	0.0448	0.0471	0.0456	0.0505	0.0467
	(0.0427)	(0.0427)	(0.0426)	(0.0426)	(0.0426)	(0.0424)	(0.0427)	(0.0426)
Experience in Using Mobile Payments	0.0345	0.0326	0.0364	0.0336	0.0349	0.0340	0.0393	0.0359
	(0.0485)	(0.0488)	(0.0485)	(0.0488)	(0.0486)	(0.0489)	(0.0485)	(0.0487)
COVID Deaths	0.0185**	0.0177**	0.0183**	0.0177**	0.0190**	0.0163**	0.0184**	0.0171**
	(0.0078)	(0.0081)	(0.0078)	(0.0078)	(0.0078)	(0.0080)	(0.0078)	(0.0078)
Shadow Economy	–0.0022	–0.0019	–0.0014	–0.0018	–0.0026	–0.0039	–0.0026	–0.0018
	(0.0063)	(0.0063)	(0.0066)	(0.0063)	(0.0063)	(0.0065)	(0.0065)	(0.0063)
Number of EFT-POS Terminals per Thousand People	–0.0036	–0.0034	–0.0035	–0.0034	–0.0036	–0.0027	–0.0036	–0.0020
	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Net Fear of Cash	0.4024***	0.4252***	0.3958***	0.3473***	0.3791***	0.4081***	0.4475***	0.4111***
	(0.0509)	(0.0552)	(0.0597)	(0.0591)	(0.0523)	(0.0691)	(0.0894)	(0.0505)

(*continued*)

Table I.3. (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in Habits Related to Physical Contact	0.9850***	0.9207***	1.0027***	1.0920***	0.9892***	0.8713***	0.7927***	1.0271***
	(0.0579)	(0.0639)	(0.0697)	(0.0722)	(0.0600)	(0.0771)	(0.1125)	(0.0609)
Change in Online Habits	0.1147**	0.1100**	0.1205**	0.0797	0.1145**	0.1309**	0.2220**	0.1049**
	(0.0475)	(0.0519)	(0.0548)	(0.0618)	(0.0489)	(0.0619)	(0.0917)	(0.0485)
Net Fear of Cash × D_Scand	–0.0902							
	(0.0926)							
Change in Habits Related to Physical Contact × D_Scand	–0.0089							
	(0.1250)							
Change in Online Habits × D_Scand	–0.0875							
	(0.0965)							
Net Fear of Cash × D_Deaths		–0.1036						
		(0.1037)						
Change in Habits Related to Physical Contact × D_Deaths		0.2193*						
		(0.1164)						
Change in Online Habits × D_Deaths		–0.0008						
		(0.0929)						
Net Fear of Cash × D_Shadow			–0.0005					
			(0.0918)					
Change in Habits Related to Physical Contact × D_Shadow			–0.0622					
			(0.1067)					
Change in Online Habits × D_Shadow			–0.0404					
			(0.0861)					
Net Fear of Cash × D_Stringency				0.0876				
				(0.0880)				
Change in Habits Related to Physical Contact × D_Stringency				–0.1827*				
				(0.1007)				
Change in Online Habits × D_Stringency				0.0501				
				(0.0831)				
Net Fear of Cash × D_Developed					0.1346*			
					(0.0815)			
Change in Habits Related to Physical Contact × D_Developed					–0.0330			
					(0.0996)			
Change in Online Habits × D_Developed					–0.0442			
					(0.0823)			
Net Fear of Cash × D_PD						–0.0228		
						(0.0898)		

(continued)

Table I.3. (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in Habits Related to Physical Contact × D_PD						0.2526**		
						(0.1036)		
Change in Online Habits × D_PD						–0.0494		
						(0.0834)		
Net Fear of Cash × D_UA							–0.0760	
							(0.1038)	
Change in Habits Related to Physical Contact × D_UA							0.2548**	
							(0.1278)	
Change in Online Habits × D_UA							–0.1479	
							(0.1022)	
Net Fear of Cash × D_Terminals								–0.1018
								(0.1404)
Change in Habits Related to Physical Contact × D_Terminals								–0.2499*
								(0.1340)
Change in Online Habits × D_Terminals								0.0289
								(0.1226)
Constant	–1.2376***	–1.2580***	–1.2612***	–1.2472***	–1.2340***	–1.2292***	–1.2389***	–1.2904***
	(0.3119)	(0.3112)	(0.3142)	(0.3113)	(0.3115)	(0.3137)	(0.3132)	(0.3123)
Observations	5,504	5,504	5,504	5,504	5,504	5,504	5,504	5,504
chi2	597.5	563.9	567.9	608.9	663.7	616.1	561.1	546.2
p	0	0	0	0	0	0	0	0
r2_p	0.223	0.224	0.223	0.224	0.223	0.225	0.225	0.224

Note: This table reports egression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2 and in Table I.1. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Appendix J

Table J.1. Modeling the Switch to Cashless Payments during the Pandemic (probit estimates)

	(1)	(2)	(3)
Gender	0.1054**	0.0906*	0.0952**
	(0.0465)	(0.0470)	(0.0472)
Location Size	0.0164	0.0091	0.0111
	(0.0151)	(0.0153)	(0.0154)
Age	0.0029*	0.0039**	0.0038**
	(0.0015)	(0.0016)	(0.0016)
Cards & Mobile	0.4067***	0.4529***	0.4450***
	(0.0782)	(0.0789)	(0.0788)
Anonymity	–0.0346*	–0.0760***	–0.0671***
	(0.0205)	(0.0210)	(0.0211)
Convenience of Cashless	0.0043	–0.0169	–0.0140
Payments	(0.0328)	(0.0339)	(0.0339)
Safety of Cashless Payments	0.0719**	0.0748**	0.0678*
	(0.0363)	(0.0364)	(0.0366)
Access to Cashless Payments	0.0138	–0.0234	–0.0201
Technologies	(0.0326)	(0.0332)	(0.0334)
Ease of Use of Cashless	0.0933**	0.1008***	0.0953**
Technologies	(0.0367)	(0.0373)	(0.0374)
Control over Finance with	0.0078	–0.0117	–0.0134
Cashless Payments	(0.0324)	(0.0328)	(0.0331)
Literacy in Using Mobile Apps	0.2323***	0.2248***	0.2233***
	(0.0285)	(0.0286)	(0.0287)
Experience in Using Computer	0.0397*	0.0110	0.0140
Payments	(0.0219)	(0.0220)	(0.0222)
Experience in Using Mobile	0.0253	0.0082	0.0101
Payments	(0.0271)	(0.0280)	(0.0278)
COVID Deaths	0.0150***	0.0108**	0.0112**
	(0.0044)	(0.0045)	(0.0045)
Shadow Economy	–0.0081**	–0.0117***	–0.0122***
	(0.0035)	(0.0035)	(0.0035)
Number of EFT-POS Terminals	0.0019	0.0001	0.0006
per Thousand People	(0.0015)	(0.0015)	(0.0016)
Net Fear of Cash	0.1718***		0.1495***
	(0.0233)		(0.0237)
Change in Habits Related to		0.2877***	0.2749***
Physical Contact		(0.0249)	(0.0250)
Change in Online Habits		0.0599**	0.0601**
		(0.0239)	(0.0240)
Constant	–0.6550***	–0.3842**	–0.4484**
	(0.1705)	(0.1742)	(0.1748)
Observations	5,504	5,504	5,504
chi2	374.5	433.7	479.1
p-value	0	0	0
McFadden's Pseudo R-squared	0.0887	0.109	0.117

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table J.2. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (probit estimates)

	(1)	(2)	(3)
Gender	0.1136**	0.0895*	0.0966*
	(0.0475)	(0.0495)	(0.0501)
Location Size	0.0164	0.0040	0.0072
	(0.0153)	(0.0161)	(0.0162)
Age	0.0015	0.0030*	0.0025
	(0.0016)	(0.0017)	(0.0017)
Cards & Mobile	0.3277***	0.4430***	0.4256***
	(0.0831)	(0.0845)	(0.0847)
Anonymity	0.0059	–0.0789***	–0.0680***
	(0.0210)	(0.0227)	(0.0230)
Convenience of Cashless Payments	0.0405	0.0145	0.0151
	(0.0336)	(0.0360)	(0.0364)
Safety of Cashless Payments	0.1437***	0.1588***	0.1520***
	(0.0375)	(0.0405)	(0.0407)
Access to Cashless Payments Technologies	0.0306	–0.0457	–0.0384
	(0.0339)	(0.0373)	(0.0379)
Ease of Use of Cashless Technologies	0.1110***	0.1365***	0.1277***
	(0.0382)	(0.0413)	(0.0418)
Control over Finance with Cashless Payments	0.0729**	0.0353	0.0341
	(0.0329)	(0.0354)	(0.0360)
Literacy in Using Mobile Apps	0.0958***	0.0797***	0.0757***
	(0.0286)	(0.0302)	(0.0305)
Experience in Using Computer Payments	0.0737***	0.0225	0.0290
	(0.0233)	(0.0240)	(0.0245)
Experience in Using Mobile Payments	0.0444	0.0193	0.0224
	(0.0278)	(0.0287)	(0.0288)
COVID Deaths	0.0173***	0.0097**	0.0107**
	(0.0045)	(0.0046)	(0.0046)
Shadow Economy	0.0065*	–0.0010	–0.0012
	(0.0036)	(0.0037)	(0.0037)
Number of EFT-POS Terminals per Thousand People	0.0004	–0.0029*	–0.0021
	(0.0015)	(0.0016)	(0.0016)
Net Fear of Cash	0.2617***		0.2273***
	(0.0253)		(0.0270)
Change in Habits Related to Physical Contact		0.5853***	0.5690***
		(0.0304)	(0.0307)
Change in Online Habits		0.0605**	0.0614**
		(0.0258)	(0.0262)
Constant	–1.0988***	–0.6081***	–0.6986***
	(0.1734)	(0.1804)	(0.1830)
Observations	5,504	5,504	5,504
chi2	436.8	587.3	609.2
p-value	0	0	0
McFadden's Pseudo R-squared	0.122	0.203	0.221

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

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Bank Rollover Risk and Liquidity Supply Regimes*

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The maturity mismatch between their short-term financing and long-term lending exposes banks to the risk of rolling over their funding. Such a rollover risk is sufficient on its own to cause a panic at the bank level and have ripple effects on the banking system as a whole. We propose a new indicator that helps central banks monitor rollover risk and thus design liquidity support operations when needed. Building on forward rates, our rollover risk indicator (RRI) captures the way banks price the risk of not being able to obtain funding at the horizon of specific interest rate derivatives. We show that our RRI has a better predictive power for economic growth and bank lending than usual bank credit spreads. In addition, our indicator helps to contrast three liquidity regimes (crisis, moderate, and abundant), which coincide with the levels of excess liquidity supplied by central banks.

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1. Introduction

The maturity mismatch between short-term funding and long-term lending exposes banks to *rollover risk*. Rollover risk refers to the risk of rolling over a maturing financial debt obligation. In good times, such a risk is relatively weak because short-term debt displays high liquidity and low risk. In bad times, when bank assets are more volatile and may dry up, short-term debt generates significant rollover risk and affects future investment incentives (Diamond and Rajan 2001; Acharya, Gale, and Yorulmazer 2011; Diamond and He 2014; Morris and Shin 2016). Rollover risk is sufficient on its own to cause a panic at the bank level and have ripple effects on the banking system as a whole (Kacperczyk and Schnabl 2010; Gorton and Metrick 2012; Covitz, Liang, and Suarez 2013; Filipović and Trolle 2013; Copeland, Martin, and Walker 2014; Gallitschke, Seifried, and Seifried 2017; Bernanke 2018). In such adverse scenarios, central banks may decide to supply public liquidity when private liquidity vanishes, following the Thornton (1802)-Bagehot (1873) principle. By providing liquidity to institutions in large amounts, they can match the panic-driven demands for liquidity and avoid disruptions to payments and credit intermediation, allowing continuity in the supply of bank credit.[1] Measuring and monitoring rollover risk in real time is thus fundamental for central banks to design operations for liquidity support.

In this paper, we propose a new daily indicator of rollover risk for large banks, which is based on forward interest rates.[2] Future

[1]See among others, Holmström and Tirole (1998), Rochet and Vives (2004), Brunnermeier (2009), Freixas, Martin, and Skeie (2011), Brunnermeier and Sannikov (2014), Calomiris, Flandreau, and Laeven (2016), and Bernanke (2018). For instance, Bernanke (2018) shows that the depth of the 2007–09 financial crisis is mainly due to the supply side of the credit market and, specifically, to the liquidity drought in the money market. In other words, preventing liquidity from drying up in the market may have reduced the depth of the recession and the accumulation of the public debt needed to stabilize the economy through fiscal policy.

[2]Several authors show that forward rates contain information about future yields and excess bond returns (Fama and Bliss 1987; Stambaugh 1988; Cochrane and Piazzesi 2005). Recently, Engstrom and Sharpe (2019) use the difference between the six-quarter-ahead forward rate on U.S. Treasuries and the current three-month Treasury-bill rate, which they call the "near-term forward spread." Benzoni, Chyruk, and Kelley (2018) find that a change in the yield curve slope due

liquidity planning for financial institutions must take into account the possibility of losing market access, and market participants have to form expectations on how rollover costs will evolve over time. The pricing of this risk depends on banks' perception of the future economic situation and expected monetary policy decisions, among others. The interest rates at which forward contracts are negotiated (i.e., based on the agreement between two counterparties to exchange, at a settlement date in the future, two payment obligations based on two interest rates) provide a means of gauging banks' short-term interest rate expectations. Consequently, using forward rates allows us to capture the way banks price rollover risk at the horizon of specific interest rate contracts. Our so-called rollover risk indicator (RRI) may be especially useful during periods when central banks saturate markets with liquidity and serves as a good signal of the change in the stance of monetary policy. The RRI can be computed for different starting forward dates, different maturities, and different frequencies of payments (tenors). It has several desirable properties: (i) it is available at a daily frequency for the dollar, the euro, and most of the major currencies;[3] (ii) it is obtained from interbank market instruments and therefore reflects the funding cost of large banks; and (iii) it relies on widely traded interest contracts and hence accurately measures the market price of funding.

We provide evidence that the RRI helps forecast macroeconomic developments in the euro area and the United States. Over the sample from 2005 to 2019, the RRI has significant predictive content for economic activity, better than those obtained from bank credit risk measures (credit default swap and bank bond spreads).[4] This result indicates that (i) the expectations of market participants regarding the future cost of funding matters a lot for the business cycle and (ii) the information content of this indicator reflects the attitude

to a monetary policy easing, measured by the current real interest rate level and its expected path, is associated with an increase in the probability of a future recession within the next year. Nakamura and Steinsson (2018) and Hansen, McMahon, and Tong (2019) also use forward rates on long-term government bonds.

[3]Daily time series of the forward funding spreads are available for the dollar, the euro, the yen, and the British pound at https://SyRis.ch/risk-management/.

[4]Before 2007, the RRI was essentially equal to zero, as the difference in tenor was not considered material by financial institutions.

of banks towards credit supply and this attitude depends on their expected cost of funding. This might be particularly relevant when central banks supply large amounts of liquidity and the market shifts its attention to the persistence of such policies. The RRI performs well at predicting bank lending, which suggests that reducing bank funding costs can help banks feed credit markets. Interestingly, our findings highlight a funding channel of the business cycle. The supply of credit by financial intermediaries depends on the cost of funding both in the United States (where market finance dominates) and in the euro area (where banks dominate the financial system). In turn, credit supply is correlated with future economic fluctuations (Bernanke 2018).

We illustrate the usefulness of the RRI to contrast liquidity regimes in the euro area and the United States, which coincide with the levels of excess liquidity supplied by central banks. Indeed, any policy that aims at reducing uncertainty regarding the availability of future lender-of-last-resort funding for banks (e.g., by lengthening the maturity of bank debt) is expected to play a crucial role in decreasing funding costs, reducing fire-sale externalities, mitigating the markup that borrowers with urgent liquidity needs pay for immediate funding, and ultimately increasing financial intermediation by banks (He and Xiong 2012; Stein 2012; Segura and Suarez 2017; Jasova Mendicino, and Supera 2021; Bechtel, Ranaldo, and Wrampelmeyer 2023). Since the 2007–09 financial crisis, three liquidity regimes can be identified: (i) a *crisis* regime, associated with a lack of liquidity in the financial system and a strong connection between the rollover risk measured by the RRI and the credit risk measured by the credit default swap (CDS) spread, (ii) a regime of *abundant liquidity*, associated with massive central bank injections of liquidity with no uncertainty over the cost of liquidity and therefore a disconnect between liquidity/rollover and credit risks, and (iii) a regime of *moderate liquidity*, characterized by uncertainty over the expected cost of liquidity but little correlation between liquidity/rollover and credit risks. In the euro area, the crisis period lasted until the end of 2012 with the announcement of the Outright Monetary Transactions program. Since then, the liquidity provided by the European Central Bank (ECB) has been abundant. Fluctuations in credit risk, which resumed in 2015, were not reflected in the RRI. In the United States, the crisis regime corresponds to the period 2007–12, including both the 2007–09 financial crisis and the European sovereign debt crisis. The period 2013–15 is associated with the abundant liquidity regime, during which the Federal Reserve provided a massive amount of liquidity through its QE3 program. From December 2015 to the end of 2020, when our sample ends, the U.S. economy has been in a moderate liquidity regime, in which rollover risk is independent of credit risk. Hence, when COVID-19 hit financial markets in March 2020, the euro area and the United States were characterized by a different liquidity regime. The euro area still stood in an abundant liquidity regime while the United States was in a moderate liquidity regime. Not surprisingly, the pandemic triggered much larger spikes in the RRI in the United States than in the euro area, as would be expected given the very different prevailing liquidity conditions.[5]

The remainder of the paper is organized as follows. In Section 2, we define the rollover risk indicators and explain how to construct them using interbank market data. In Section 3, we evaluate the ability of these indicators and some other well-established indicators of bank liquidity and credit risk to predict future real activity and bank lending. In Section 4, we analyze the link between the RRI and central bank liquidity regimes in the euro area and the United States since 2008. The final section concludes the paper.

2. Rollover Risk Indicator

This section precisely describes the concept and the construction of the RRI and presents the underlying interbank data used to measure it.

2.1 Definition

Rollover risk can be illustrated by considering the two following strategies. On the one hand, bank A borrows at the three-month interbank offered rate (IBOR). At maturity, the bank repays the notional plus the fixed rate. On the other hand, bank B borrows

[5]It is consistent with Copeland, Duffie, and Yang (2021), who show that only with a substantial amount of reserves do the large dealer banks avoid intraday liquidity stress and provide liquidity efficiently to wholesale funding markets.

cash on a daily basis at the overnight federal funds rate for three months and simultaneously enters into an overnight index swap (OIS), receiving the floating rate (the overnight effective federal funds rate) and paying the fixed rate (the OIS three-month rate). In both cases, the interest rate for the three-month funding is set in advance, and therefore no interest rate risk is involved. However, in a stressed market, banks A and B would face different situations. For bank A, the funding is guaranteed, as the contract runs until the end of the three months. Bank B, in contrast, may be unable to roll its funding if it cannot find a counterpart and therefore may become illiquid and have to accept higher prices to access funding liquidity. This situation may happen in the event of a market freeze (funding liquidity risk) or if the lender demands a higher credit spread (credit risk). Because bank B may suffer from such rollover risk, it pays a lower interest rate than bank A. Therefore, the funding based on a three-month IBOR contract commands a higher interest rate, which generates the observed tenor spread between the IBOR and the OIS rate. Because liquidity and credit risks are negligible for OIS contracts, the rollover risk corresponds to the risk of the three-month floating leg.

More generally, rollover risk depends on the tenor of the floating leg. The tenor of a financial contract refers to the frequency with which coupon payments are exchanged. For instance, for a one-year swap with a 3-month tenor, bank A will pay the fixed rate every 3 months for 12 months, whereas bank B will pay the floating 3-month rate. The tenor therefore specifies the maturity of the floating rate and the frequency of the cash flows. Most contracts on interbank markets are linked to the IBOR of a specific tenor (typically, 1, 3, 6, or 12 months). For a given bank, interest rate instruments with the same maturity but different underlying tenors are characterized by different liquidity or credit risk premiums, reflecting the different views and interests of the market counterparts.

Before the financial crisis, rollover risk was close to nil and was therefore neglected. During the financial crisis, there was a disconnection of the IBOR from the OIS rate with the same maturity, such that this spread is now considered an indicator of market stress or panic. It is usually interpreted as reflecting rollover risk, which combines funding liquidity risk and credit risk.

A limitation of IBOR-OIS spread is that it measures the current funding cost but does not inform on the expected rollover risk. In contrast, forward rates allow us to extract such market participants' expectations from the yield curve. We define the three-month rollover risk indicator (RRI), starting in three months for the three-month tenor as follows:

$$RRI^{(3m)}_{3m,3m} = F^{(3m)}_{3m,3m} - F^{(ois)}_{3m,3m}, \tag{1}$$

where the forward rate $F^{(3m)}_{3m,3m}$ is computed from the three-month tenor curve and the forward rate $F^{(ois)}_{3m,3m}$ is computed from the OIS curve. As rollover risk is negligible for the OIS curve, the RRI measures the rollover risk originating from the three-month tenor curve.

For some starting dates, maturities, and tenors, the forward rates can be obtained directly from market data when the relevant forward rate agreements (FRAs) or interest rate swaps (IRS) are quoted. This is the case, for instance, of the $RRI^{(3m)}_{3m,3m}$ introduced above. However, in general, as not all starting dates, maturities, and tenors are available on interbank markets, one needs to construct a complete yield curve for each tenor to compute the RRI. We briefly describe this approach in the next section.

2.2 Data and Construction

Our rollover risk indicator measures the expected cost of funding of large banks. It is constructed using interbank data, i.e., deposits, forward rate agreements (FRAs), overnight index swaps (OIS), and interest rate swaps (IRS). For major currencies, these instruments correspond to very wide markets and exhibit extremely large turnover. As the BIS triennial report reveals (Bank for International Settlements 2019), as of the first half of 2019 the notional amount outstanding for all currencies represents USD 89 trillion on the FRA market and 389.3 trillion on the swap market (including both OIS and IRS). Gross market values are equal to USD 232 billion and 7,793 billion, respectively.[6] Daily turnover also posts impressive numbers. On a net-net basis, as of April 2019, the daily turnover

[6]For comparability, all foreign exchange contracts had a notional amount outstanding of USD 98.7 trillion and a gross market value of 2,229 billion.

on the FRA and swap segments amounts to USD 1,902 billion and 4,146 billion, respectively. EUR and USD instruments are by far the largest segments of the market: overall, they represent respectively 22 percent and 54 percent of all interest rate contracts in terms of gross market values and 52 percent and 22 percent of total turnover.

We collected from Bloomberg quotes for all EUR and USD interest rate instruments on the interbank markets. These instruments include bank deposits (unsecured euro overnight index average (EONIA) and federal funds) and FRA, OIS, IRS, and basis swaps for all available tenors. To compute the forward yield curve of a given tenor in a given month, we rely on the literature dealing with the multicurve environment that followed the 2007–09 financial crisis (see, among others, Henrard 2007, 2010; Ametrano and Bianchetti 2009; Bianchetti 2009; and Mercurio 2009, 2010). Two types of yield curves are constructed: a *discounting curve*, which is used to compute the present value of future cash flows, and several *forwarding curves*, which are used to compute the future cash flows corresponding to a given tenor. The discounting curve is based on OIS contracts with different maturities (and sufficient liquidity). It can be interpreted as the curve corresponding to the absence of liquidity and credit risks.[7] The forwarding curves, also called funding curves, correspond to different tenors (from 1 to 12 months). For instance, the three-month funding curve in the United Sates is based on the three-month IBOR, a sequence of three-month FRA, and a sequence of IRS with a three-month tenor.

The discounting and forwarding curves are constructed using a standard optimization procedure. The estimation of the yield curve

[7]OIS discounting is relevant in the absence of counterparty risk or in the case of derivatives that are collateralized on a daily basis (Mercurio 2009, 2010). Most derivatives traded over the counter have ISDA (International Swaps and Derivatives Association) master agreements. These agreements usually include a credit support annex (CSA) that specifies the protections from which the derivatives benefit. Typical CSAs involve daily collateralization, which means that margin calls can take place on a daily basis. Alternatively, in the case of a contract with a general counterparty or without collateral, a discounting curve based on IBOR may be more relevant because it reflects the risk of the interbank sector as a whole (Ametrano and Bianchetti 2009; Bianchetti 2009). Hull and White (2013) provide theoretical arguments that, in all cases, OIS discounting should be preferred. We follow this advice and use the OIS curve as the unique discounting curve. The credit risk in an OIS is the risk of a possible default by one of the counterparties on an overnight loan and is usually viewed as negligible.

of a given tenor produces a sequence of three-month forward rates that minimize the difference between theoretical and market prices of the available instruments, while maintaining sufficient smoothing of the yield curve.

Our collected data start in January 1999 and end in December 2020. Between 1999 and 2004, the number of instruments available for each tenor is not sufficient to compute a yield curve. As a consequence, we construct tenor yield curves at a daily frequency from January 2005 onward for the United States and the euro area. As put forward by several papers (Ametrano and Bianchetti 2009; Bianchetti 2009; Mercurio 2009), tenor spreads were negligible before 2007. Between 2005 and July 2007, the average $RRI^{(3m)}_{3m,3m}$ is equal to 2.5 basis points (bp) in the United States and 3.2 bp in the euro area, while the average $RRI^{(6m)}_{6m,6m}$ is equal to –1.4 bp in the United States and 0.7 bp in the euro area.

The estimated yield curves fit the observed prices very well.[8] Indeed, between 2005 and 2009, the relative error in reproducing observed prices is on average equal to 3 bp and 1.7 bp for the three-month curve in the United States and the euro area, respectively (1.2 bp and 0.8 bp for the six-month curve). After 2009, the relative error is on average below 10.5 bp in the United States and below 0.25 bp in the euro area for both tenor curves.[9] Tenor yield curves are available at a daily frequency from January 2005 onward for the euro area and the United States, although we start our analysis in January 2007. Data are available upon request and are updated regularly.

In summary, the RRI is based on highly liquid instruments and cover a very large spectrum of maturities. The construction of the tenor yield curves is easily performed at a daily frequency, for the one-, three-, and six-month tenors. In addition, the resulting curves

[8]See Appendix A for additional details on the instruments used for the construction of yield curves and results on the quality of the fit.

[9]These numbers are below those reported by Goldberg (2020) for the U.S. Treasury curve. The relative error of the monthly Treasury yields between September 1990 and May 2017 is measured at 3.4 bp on average. He also finds a peak in 2008–09 during the subprime crisis. The fact that the relative error is lower for interbank curves than it is for U.S. Treasury curves is not surprising because interbank instruments are far more traded, leaving lower arbitrage opportunities.

closely match observed prices, so that the RRI reflects true market conditions accurately and timely.

3. Predictive Content of the RRI

In this section, we investigate whether macroeconomic and banking variables are mainly driven by rollover or credit risks by comparing the predictive ability of the RRI with that of widely used indicators of bank credit risks.

3.1 Bank Credit Risk Indicators

We consider two indicators of bank credit risks: the credit default swap spread and the bank bond credit spread. The first measure relies on banks' CDS contracts. As they directly measure the risk of default of banks, these contracts are a standard way to measure the extent of a bank's credit risk. One limitation of the approach is that CDS contracts are usually written on individual institutions and the aggregation over banks may introduce some biases because of the interdependence between banks. As an index representative of banks' CDS spreads, we use data from ICE Credit Market Analysis (CMA), which collects quotes from the largest and most active credit investors in the over-the-counter (OTC) market. These indices are based on five-year maturity senior unsecured debt, as these contracts are usually considered the most liquid. The data start in January 2004.[10]

The second measure relies on bonds issued by banks and is calculated as the difference between the corporate yield of a given maturity and the corresponding government bond yield with similar maturity. This approach was initiated by Gilchrist and Zakrajšek (2012a) (GZ) for U.S. data and Gilchrist and Mojon (2018) (GM) for European data. The challenge of this approach is related to the structure of the bond market for banks because it may suffer from some lack of liquidity, at least for some financial intermediaries.

[10] Mayordomo, Ignacio Peña, and Schwartz (2014) compare several databases collecting CDS prices. They report that CMA quotes lead the price discovery process. We also estimate predictive regressions with Thomson Reuters indices, starting in December 2007, and reach very similar conclusions.

Indeed, total debt securities represent a relatively small fraction of total bank financing.[11] The GZ index is constructed as follows. For a given month t and a given firm i, the market price of the outstanding bond security k is used to compute its yield $y_{i,t}[k]$. Then, the individual credit spread is computed by subtracting the yield of a Treasury security of the same maturity $y_{f,t}[k]$, so that the credit spread is written as $S_{i,t}[k] = y_{i,t}[k] - y_{f,t}[k]$. Finally, the index is the (unweighted) average over maturities and over firms of the individual credit spreads: $S_t^{GZ} = \frac{1}{N_t}\sum_i \sum_k S_{i,t}[k]$, where N_t is the number of bond/firm observations in month t. For the GM index in the euro area, the individual credit spread is calculated by subtracting the German bund zero-coupon interest rate of a similar maturity. The GM credit risk indicator is then calculated as the (weighted) average of the individual credit spreads, where weights correspond to the ratio of the market value of the security relative to the total market value of all bonds in the sample.[12]

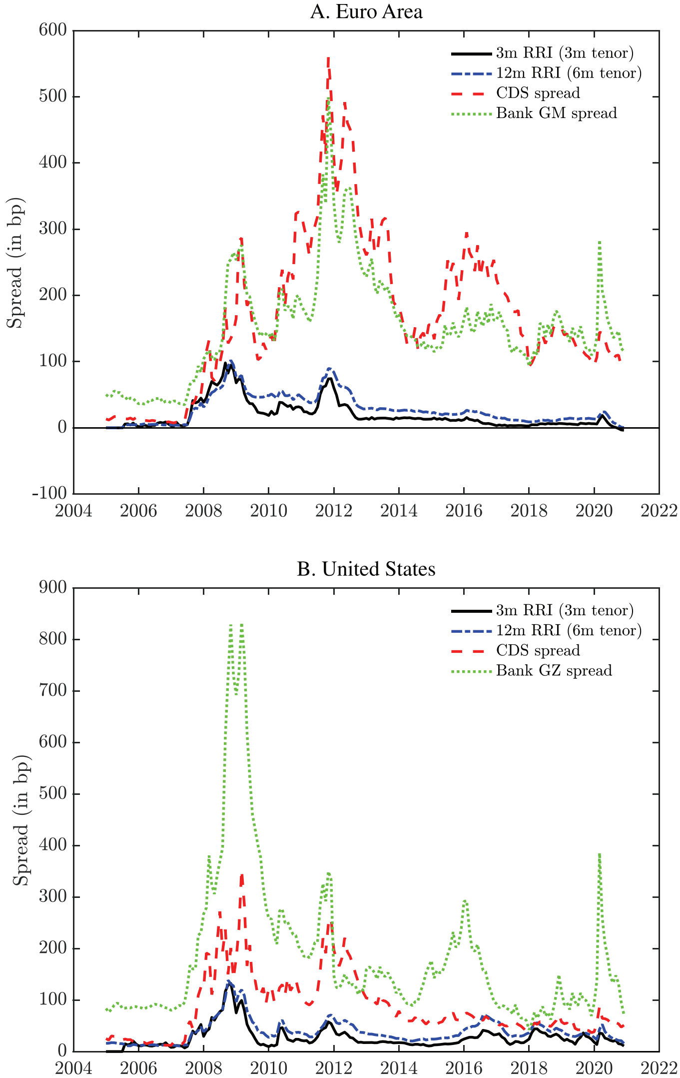
Figure 1 displays the monthly evolution of the 3-month RRI (3-month tenor) (denoted by $RRI^{(3m)}_{3m,3m}$) and 12-month RRI (6-month tenor) ($RRI^{(6m)}_{12m,12m}$), the CDS spread, and the GM and GZ spreads for the euro area and the United States between 2005 and 2020. We observe some substantial differences between the indicators across the two zones.

In the euro area (panel A), the CDS and GM spreads have similar levels and temporal evolutions: both indicators sharply increase during the 2008–09 crisis (to a maximum of 300 bp in March 2009), and they experience an even more pronounced increase in 2011–12 during the sovereign debt crisis (from 200 bp to a maximum of 500 bp in November–December 2011). We note that the CDS spread also jumps at the end of 2015, with a peak in February

[11]Long-term debt securities represent on average less than 2 percent of commercial banks' total liabilities in the United States.

[12]The GZ spread for banks covers the period from January 1985 to December 2012 and has not been updated since, while the spread for non-financial firms covers the period from January 1973 to November 2019 (Gilchrist and Zakrajšek 2012a). We have estimated the linear relation between the two indicators between 2005 and 2012 and used this relation to update the bank spread between 2013 and 2019. We investigated other approaches and obtained similar results.

Figure 1. Rollover and Credit Risk Indicators



Note: Panel A displays the bank credit risk indicators for the euro area: the 3-month and 12-month RRI, the CDS spread, and the GM spread (Gilchrist and Mojon 2018). Panel B displays the bank credit risk indicators for the United States: the 3-month and 12-month RRI, the CDS spread, and the bank GZ spread (Gilchrist and Zakrajšek 2012b). The sample periods run from January 2005 to December 2020.

2016, while the GM spread barely increases. Both tenor spreads also increase substantially during the subprime crisis (with a maximum of 100 bp for the 3- and 12-month RRIs). The impact of the sovereign debt crisis is similar, as the spreads reach 75 bp and 90 bp, respectively. In the recent period, the evolution is smoothed, and the tenor spreads do not exceed 25 bp. In contrast to the United States, the correlation between the RRI and the credit spreads is relatively low. The correlation is below 50 percent with the CDS spread and below 70 percent with the GM spread. As expected, the correlation between the CDS and GM spreads is much higher, approximately 90 percent.

In the United States (panel B), the four indicators exhibit a peak during the financial crisis but with different timings. The 3- and 12-month RRIs reach their maximum values in October 2008 just before the GZ spread (November), while the CDS spread peaks in March 2009. The four indicators also substantially increase in November–December 2011 with very similar timings. We note, however, that the CDS spread is almost as high as the maximum attained in 2008–09. Finally, there is a surge in the GZ spread in January 2016 that is not associated with significant movement in the other spreads. Note that the 3- and 12-month RRIs display similar correlation patterns. They have high correlation with the GZ spread (77 percent and 79 percent, respectively) and relatively lower correlation with the CDS spread (65 percent and 70 percent, respectively). All this evidence suggests that the indicators may capture different phenomenons.

In summary, in the euro area, the series are likely to exhibit different predictive properties because of their different temporal evolution. In contrast, in the United States, the similarity between the series suggests that predictive ability should be more similar across indicators.[13]

[13] We also considered the indicator of broker-dealers liquidity supply constructed by Goldberg (2020). This measure is based on broker-dealers trading positions in Treasury bonds and the deviations of Treasury yields from a fitted yield curve. We have tested the ability of this indicator to predict real activity and bank lending variables for the United States. The results based on this indicator are reported in Appendix B.

3.2 Methodology

We now adopt the following methodology to measure the ability of liquidity and credit spreads to predict real economic activity (Gilchrist and Zakrajšek 2012a, Gilchrist and Mojon 2018, and Goldberg 2020). Let $\Delta^h y_{t+h} = \log(Y_{t+h}/Y_t)$ measure the h-quarter-ahead percent change in the variable of interest Y_t. The predictive equation is written as

$$\Delta^h y_{t+h} = \alpha_h + \beta_h S_t + \gamma_h \Delta^h y_t + \delta_{1,h} r_t + \delta_{2,h} term_t + \epsilon_{t+h}, \quad (2)$$

where S_t is the spread indicator and ϵ_{t+h} is an error term. As control variables, we include the lag of the variable of interest, as observed at date t; the real short-term interest rate (r_t); and the term premium ($term_t$).[14]

As for risk indicators, we consider various measures of rollover risk, the CDS spread, and the GZ/GM spread. Regarding funding spreads, we investigate the role of their tenor and maturity in determining their predictive ability. We report results for RRIs with one-, three-, and six-month tenors, for different starting dates and maturities. Specifically, we test 3-, 6-, and 12-month RRIs with x-month tenor, denoted by $RRI^{(xm)}_{(3m,3m)}$, $RRI^{(xm)}_{(6m,6m)}$, and $RRI^{(xm)}_{(12m,12m)}$. We also consider alternative combinations of starting dates and maturities such as a 12-month forward spread starting in 6 months ($RRI^{(xm)}_{(6m,12m)}$) or a 12-month forward spread starting in 24 months ($RRI^{(xm)}_{(24m,12m)}$), to investigate the importance of the forward-looking component. We do not report all of the results for the sake of space and focus on results based on 3-month $RRI^{(xm)}_{(3m,3m)}$ and 12-month forward rates $RRI^{(xm)}_{(12m,12m)}$. All results are available upon request.

We consider four real activity variables (real GDP, real consumption, real investment, and the unemployment rate) and four measures of bank lending (total bank lending, consumer loans, real estate

[14]The real interest rate is measured as the short-term rate (federal funds rate in the United States, EONIA rate in the euro area) minus the 12-month inflation rate. The term spread is measured as the difference in yields on 10-year AAA sovereign bonds minus the short-term interest rate (federal funds or EONIA rates).

loans, and commercial and industrial loans). The results related to real activity are reported in Tables 1 and 2 for the euro area and the United States, respectively. The results related to bank lending are reported in Tables 3 and 4. In all tables, we focus on two- and four-quarter predictability. We do not report estimates of γ_h, $\delta_{1,h}$, and $\delta_{2,h}$ to save space.[15]

We perform our analysis from January 2005 to December 2019. This period covers a single business cycle, the origin of which was clearly in the financial sector. We do not include data prior to 2005 because tenor spreads were negligible before 2007 and could not be computed from multiple yield curves before 2004. We do not include data for 2020 to avoid the regressions being polluted by the extreme shock associated with the COVID-19 pandemic, which caused an unprecedented drop in real activity. This (relatively) short sample prevents us from performing a rolling-window analysis or estimates based on subsamples to evaluate the specific role played by some episodes, such as the 2007–09 financial crisis.

3.3 Predicting Real Activity

3.3.1 GDP Growth

We begin with the ability of the spread indicators to predict real GDP growth. As Table 1 (panel A) reveals, the RRI is the best predictor of euro-area GDP growth. For instance, the adjusted R^2 values are equal to 73 percent and 70 percent for the two- and four-quarter horizons, respectively, for the three-month RRI (three-month tenor). The spreads based on other starting dates and other tenors exhibit similar results, with negative and highly significant coefficients (all p-values are below 0.1 percent). On average, an increase of 10 bp in the three-month RRI predicts a decrease in GDP of 0.5 percent and 0.9 percent in the subsequent quarters. Credit spreads have much lower predictive performance. For the GM spread, the adjusted R^2 is approximately equal to 38 percent and 27 percent, for the two- and four-quarter horizons, respectively, also with highly significant

[15] Appendix B reports all results, with one-, two-, and four-quarter horizons, all parameter estimates (including γ_h, $\delta_{1,h}$, and $\delta_{2,h}$), and Goldberg (2020) indicators of liquidity supply and demand for U.S. broker-dealers.

Table 1. Predicting Euro-Area Real Activity Variables Using the RRI and Credit Spreads

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			**12-Month RRI** $\left(RRI^{(xm)}_{12m,12m}\right)$			**CDS Spread**	**GM Spread**
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
A. Real GDP Growth								
Variables in $t-2$								
Variable	–8.421	–5.109	–3.042	–9.949	–6.353	–5.067	–0.414	–1.007
(t-stat)	(4.027)	(5.061)	(6.188)	(5.745)	(5.261)	(4.614)	(2.029)	(2.865)
Adj. R^2	0.0674	**0.726**	0.623	0.679	0.712	0.676	0.303	0.378
Variables in $t-4$								
Variable	–14.994	–9.084	–5.341	–16.539	–11.330	–9.125	–1.016	–2.088
(t-stat)	(5.721)	(7.863)	(5.526)	(5.471)	(7.664)	(6.676)	(2.069)	(4.259)
Adj. R^2	0.658	**0.703**	0.555	0.605	0.683	0.619	0.150	0.268
B. Real Consumption Growth								
Variables in $t-2$								
Variable	–2.874	–1.873	–0.883	–2.633	–2.319	–1.808	–0.171	–0.239
(t-stat)	(4.181)	(6.972)	(3.386)	(3.418)	(6.743)	(6.389)	(1.769)	(1.768)
Adj. R^2	0.680	**0.714**	0.634	0.630	0.705	0.684	0.572	0.556
Variables in $t-4$								
Variable	–6.633	–4.165	–2.167	–6.294	–5.186	–4.174	–0.414	–0.708
(t-stat)	(5.082)	(5.794)	(3.564)	(3.406)	(5.357)	(5.427)	(1.556)	(2.147)
Adj. R^2	0.545	**0.586**	0.464	0.458	0.576	0.542	0.313	0.311

(continued)

Table 1. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
C. Real Investment Growth								
Variables in $t-2$								
Variable	–19.083	–11.877	–7.430	–22.151	–14.830	–12.354	–1.203	–2.721
(t-stat)	(4.777)	(7.231)	(8.585)	(7.214)	(7.833)	(7.378)	(2.728)	(4.194)
Adj. R^2	0.533	**0.592**	0.561	0.547	0.575	0.569	0.190	0.315
Variables in $t-4$								
Variable	–34.784	–21.674	–12.763	–38.535	–27.418	–22.346	–2.797	–5.046
(t-stat)	(6.135)	(8.900)	(6.549)	(6.376)	(9.086)	(8.293)	(2.658)	(5.113)
Adj. R^2	0.631	**0.701**	0.577	0.589	0.691	0.647	0.214	0.321
D. Unemployment Rate Change								
Variables in $t-2$								
Variable	2.627	1.612	0.979	2.977	2.021	1.610	0.111	0.278
(t-stat)	(6.548)	(7.145)	(10.465)	(8.497)	(7.246)	(5.687)	(1.822)	(2.716)
Adj. R^2	0.831	**0.841**	0.805	0.832	0.838	0.810	0.589	0.628
Variables in $t-4$								
Variable	6.168	3.724	2.109	6.622	4.694	3.726	0.390	0.753
(t-stat)	(10.153)	(13.622)	(8.564)	(7.612)	(11.652)	(9.580)	(2.138)	(4.422)
Adj. R^2	0.785	**0.800**	0.665	0.730	0.789	0.716	0.317	0.400

Note: This table reports predictive regressions for euro-area real activity variables. Predictive horizons are two and four quarters. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. The sample period runs from January 2005 to December 2019.

Table 2. Predicting U.S. Real Activity Variables Using the RRI and Credit Spreads

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread
	1m	3m	6m	1m	3m	6m		
A. Real GDP Growth								
Variables in $t-2$								
Variable	–4.907	–4.023	–2.597	–5.942	–4.531	–3.355	–0.969	–0.427
(t-stat)	(4.770)	(3.451)	(4.388)	(3.785)	(3.117)	(2.914)	(2.257)	(2.167)
Adj. R^2	0.519	0.502	0.412	**0.523**	0.461	0.377	0.276	0.208
Variables in $t-4$								
Variable	–6.706	–5.760	–4.269	–8.819	–7.083	–5.694	–2.329	–1.099
(t-stat)	(4.329)	(4.209)	(4.043)	(4.587)	(3.976)	(3.605)	(2.580)	(4.239)
Adj. R^2	0.426	0.443	0.440	**0.481**	0.453	0.387	0.428	0.319
B. Real Consumption Growth								
Variables in $t-2$								
Variable	–2.010	–1.665	–1.102	–2.995	–2.153	–1.531	–0.750	–0.068
(t-stat)	(3.791)	(4.010)	(3.062)	(4.573)	(4.071)	(3.941)	(3.576)	(0.605)
Adj. R^2	0.557	0.557	0.542	**0.591**	0.566	0.540	0.575	0.473
Variables in $t-4$								
Variable	–4.109	–3.661	–2.732	–6.077	–4.928	–3.917	–2.138	–0.337
(t-stat)	(3.715)	(4.325)	(3.414)	(4.281)	(4.300)	(4.340)	(4.265)	(1.913)
Adj. R^2	0.503	0.517	0.523	0.557	0.547	0.511	**0.613**	0.394

(*continued*)

Table 2. (Continued)

	3-Month RRI $\left(\boldsymbol{RRI}^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(\boldsymbol{RRI}^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
C. Real Investment Growth								
Variables in $t-2$								
Variable	–15.654	–12.178	–8.245	–17.831	–13.406	–10.142	–2.343	–1.929
(t-stat)	(4.275)	(2.783)	(3.032)	(2.997)	(2.400)	(2.072)	(1.591)	(1.770)
Adj. R^2	**0.691**	0.634	0.578	0.649	0.585	0.526	0.413	0.470
Variables in $t-4$								
Variable	–23.489	–18.088	–12.078	–27.543	–20.566	–14.891	–5.238	–2.967
(t-stat)	(4.939)	(3.551)	(3.757)	(3.650)	(2.917)	(2.332)	(1.700)	(3.135)
Adj. R^2	**0.597**	0.558	0.522	0.577	0.526	0.457	0.433	0.435
D. Unemployment Rate Change								
Variables in $t-2$								
Variable	2.531	2.083	1.474	3.033	2.369	1.879	0.382	0.417
(t-stat)	(7.307)	(4.187)	(5.548)	(4.539)	(3.300)	(2.727)	(1.683)	(2.790)
Adj. R^2	**0.821**	0.787	0.764	0.800	0.751	0.703	0.574	0.670
Variables in $t-4$								
Variable	4.825	3.922	2.713	5.907	4.646	3.693	1.105	0.681
(t-stat)	(6.801)	(5.188)	(6.051)	(5.313)	(4.244)	(3.661)	(1.816)	(4.356)
Adj. R^2	**0.702**	0.683	0.664	0.697	0.655	0.591	0.471	0.545

Note: This table reports predictive regressions for U.S. real activity variables. Predictive horizons are two and four quarters. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. The sample period runs from January 2005 to December 2019.

Table 3. Predicting Euro-Area Bank Lending Variables Using the RRI and Credit Spreads

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			**12-Month RRI** $\left(RRI^{(xm)}_{12m,12m}\right)$			**CDS Spread**	**GM Spread**
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
				A. Bank Credit Growth				
Variables in $t-2$								
Variable	–6.348	–3.566	–2.045	–6.929	–4.515	–3.604	–0.755	–1.17
(t-stat)	(5.864)	(6.459)	(4.936)	(7.469)	(6.951)	(5.193)	(3.741)	(3.113)
Adj. R^2	**0.845**	0.839	0.822	0.843	0.839	0.831	0.802	0.825
Variables in $t-4$								
Variable	–19.168	–11.199	–6.268	–20.592	–14.279	–11.32	–2.244	–3.282
(t-stat)	(5.662)	(7.938)	(6.030)	(8.018)	(9.247)	(7.318)	(4.319)	(3.412)
Adj. R^2	0.833	0.844	0.803	0.828	**0.848**	0.836	0.761	0.791
				B. Consumer Loan Growth				
Variables in $t-2$								
Variable	–5.009	–3.055	–1.692	–5.015	–3.759	–3.154	–0.746	–1.143
(t-stat)	(4.387)	(5.610)	(4.158)	(4.666)	(5.847)	(5.095)	(2.953)	(3.539)
Adj. R^2	0.682	**0.693**	0.670	0.666	0.688	0.685	0.673	0.687
Variables in $t-4$								
Variable	–14.219	–8.388	–4.669	–14.517	–10.541	–8.533	–1.547	–2.634
(t-stat)	(7.496)	(9.119)	(6.394)	(7.516)	(9.884)	(8.187)	(2.884)	(4.667)
Adj. R^2	0.778	**0.789**	0.738	0.745	0.786	0.767	0.667	0.719

(*continued*)

Table 3. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
C. Real Estate Loan Growth								
Variables in $t-2$								
Variable	–3.644	–2.009	–1.053	–3.847	–2.586	–2.079	–0.366	–0.535
(t-stat)	(4.057)	(3.668)	(2.608)	(4.200)	(3.498)	(2.63)	(2.121)	(1.99)
Adj. R^2	**0.732**	0.726	0.706	0.724	0.727	0.719	0.696	0.696
Variables in $t-4$								
Variable	–9.978	–5.476	–2.854	–9.857	–6.946	–5.613	–1.255	–1.638
(t-stat)	(5.519)	(5.070)	(3.622)	(4.493)	(4.564)	(3.816)	(2.856)	(3.400)
Adj. R^2	**0.713**	0.697	0.648	0.677	0.696	0.679	0.651	0.641
D. C&I Loan Growth								
Variables in $t-2$								
Variable	–9.010	–5.019	–3.271	–10.042	–6.374	–5.187	–0.909	–1.712
(t-stat)	(6.533)	(7.506)	(9.637)	(9.162)	(8.339)	(8.836)	(4.155)	(4.306)
Adj. R^2	0.889	0.886	**0.903**	0.898	0.888	0.890	0.846	0.901
Variables in $t-4$								
Variable	–27.828	–16.771	–10.284	–30.724	–21.346	–17.192	–2.757	–4.833
(t-stat)	(5.920)	(10.505)	(10.413)	(10.118)	(11.908)	(12.015)	(4.369)	(4.466)
Adj. R^2	0.830	0.860	0.875	0.850	0.866	**0.876**	0.755	0.840

Note: This table reports predictive regressions for euro-area bank lending variables. Predictive horizons are two and four quarters. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. "C&I loan" means commercial and industrial loan. The sample period runs from January 2005 to December 2019.

Table 4. Predicting U.S. Bank Lending Variables Using the RRI and Credit Spreads

	3-Month RRI $\left(\boldsymbol{RRI}^{(xm)}_{3m,3m}\right)$			**12-Month RRI** $\left(\boldsymbol{RRI}^{(xm)}_{12m,12m}\right)$			**CDS Spread**	**GZ Spread**
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
A. Bank Credit Growth								
Variables in $t-2$								
Variable	–2.623	–2.832	–2.474	–3.735	–3.775	–3.704	–1.129	–0.532
(t-stat)	(1.781)	(2.323)	(3.646)	(2.117)	(2.867)	(3.734)	(1.866)	(3.262)
Adj. R^2	0.353	0.405	0.483	0.380	0.431	**0.493**	0.385	0.434
Variables in $t-4$								
Variable	–9.237	–8.063	–6.054	–11.675	–10.089	–9.055	–2.789	–1.343
(t-stat)	(6.022)	(6.749)	(9.907)	(6.028)	(7.279)	(11.004)	(2.627)	(5.803)
Adj. R^2	0.614	0.682	0.766	0.658	0.714	**0.792**	0.561	0.671
B. Consumer Loan Growth								
Variables in $t-2$								
Variable	–0.740	–2.055	–2.534	–1.791	–2.898	–3.342	–0.556	–0.734
(t-stat)	(0.284)	(1.125)	(3.592)	(0.629)	(1.590)	(2.799)	(0.839)	(4.138)
Adj. R^2	0.404	0.419	0.458	0.408	0.429	0.459	0.412	**0.489**
Variables in $t-4$								
Variable	–4.821	–6.112	–5.323	–7.255	–7.683	–8.293	–1.847	–1.802
(t-stat)	(1.446)	(2.441)	(3.128)	(1.994)	(2.625)	(3.586)	(1.559)	(4.062)
Adj. R^2	0.513	0.546	0.572	0.528	0.555	0.602	0.526	**0.650**

(*continued*)

Table 4. (Continued)

	3-Month RRI $\left(\boldsymbol{RRI}^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(\boldsymbol{RRI}^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread
	1m	**3m**	**6m**	**1m**	**3m**	**6m**		
C. Real Estate Loan Growth								
Variables in $t-2$								
Variable	–0.282	–1.066	–1.397	–1.410	–1.998	–2.208	–0.822	–0.265
(t-stat)	(0.147)	(0.662)	(1.511)	(0.585)	(1.090)	(1.567)	(1.604)	(1.235)
Adj. R^2	0.529	0.536	0.558	0.534	0.547	**0.563**	0.552	0.544
Variables in $t-4$								
Variable	–4.558	–4.978	–4.539	–7.143	–7.010	–7.144	–2.226	–1.186
(t-stat)	(1.973)	(2.605)	(3.552)	(2.411)	(3.124)	(4.246)	(2.414)	(4.567)
Adj. R^2	0.674	0.701	0.747	0.696	0.722	**0.764**	0.702	0.742
D. C&I Loan Growth								
Variables in $t-2$								
Variable	–12.384	–10.483	–7.926	–14.488	–12.263	–10.590	–3.432	–2.101
(t-stat)	(5.344)	(4.645)	(6.827)	(4.165)	(4.014)	(4.488)	(1.863)	(8.747)
Adj. R^2	0.694	0.735	0.809	0.697	0.727	0.757	0.633	**0.847**
Variables in $t-4$								
Variable	–34.528	–28.842	–20.605	–40.960	–33.598	–28.601	–8.539	–5.379
(t-stat)	(10.627)	(7.673)	(10.069)	(7.078)	(6.256)	(7.221)	(1.809)	(15.428)
Adj. R^2	0.589	0.668	0.750	0.613	0.657	0.718	0.408	**0.812**

Note: This table reports predictive regressions for U.S. bank lending variables. Predictive horizons are two and four quarters. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. "C&I loan" means commercial and industrial loan. The sample period runs from January 2005 to December 2019.

parameters. For CDS spreads, the adjusted R^2 values are below these values. The better prediction generated by the RRI is due to the ability of this indicator to anticipate the magnitude of the recession during the subprime crisis. Tenor spreads predict a more severe recession in 2008–09 than in 2012. In contrast, the CDS and GM spreads predict a more severe recession in 2012.

We obtain similar results for U.S. GDP growth (Table 2, panel A). The 12-month forward spreads (1-month tenor) have the highest predictive power for GDP growth. The adjusted R^2 values are equal to 52 percent and 48 percent, for the two- and four-quarter horizons, respectively. On average, an increase of 10 bp in the RRI predicts a decrease of 0.6 percent and 0.9 percent in GDP growth in the subsequent quarters. The parameters are all highly significant. Their magnitude increases with the forecast horizon and decreases with the tenor. Credit spreads also have relatively high adjusted R^2 values, but they remain below 28 percent for the two-quarter horizon and below 43 percent for the four-quarter horizons.

3.3.2 Consumption Growth

We now consider the ability of spread indicators to predict real consumption growth. The results reported in panel B indicate that the three-month RRI (three-month tenor) strongly outperforms the other indicators for all horizons in the euro area. For instance, for the four-quarter horizon, the adjusted R^2 is as high as 59 percent, whereas it is below 32 percent for credit spreads.

In the United States, the 12-month RRI (1-month tenor) produces the best forecast for the two-quarter horizon, with an adjusted R^2 equal to 59 percent, whereas the adjusted R^2 of the CDS spread is equal to 57.5 percent. For the four-quarter horizon, the adjusted R^2 values are equal to 56 percent and 61 percent, respectively.

3.3.3 Investment Growth

Panel C reports that in terms of predicting euro-area investment growth, the gain of using the RRI is as large for investment as for consumption. The adjusted R^2 values of the three-month RRI (three-month tenor) are equal to 59 percent and 70 percent for the two- and four-quarter horizons but only 31 percent and 32 percent for the GM spread. The results with the CDS spread are even worse (adjusted R^2 close to 20 percent). A 10 bp increase in the three-month RRI (three-month tenor) predicts, on average, a decline in investment of 1.2 percent and 2.2 percent in the subsequent quarters.

For U.S. investment growth, the three-month RRI (one-month tenor) dominates the other indicators for all horizons: the adjusted R^2 values are close to 70 percent and 60 percent for the two- and four-quarter horizons, respectively. Credit spreads produce R^2 values that are close to 40–45 percent. It is worth emphasizing that the 3-month RRI performs well for investment growth, whereas the 12-month RRI dominates for consumption growth. This result suggests that expectations play a different role for these two variables. Investment seems to be more reactive to the most recent information, while consumption is based on more forward-looking expectations.

3.3.4 Unemployment Rate

For the unemployment rate (panel D), the predictive ability of the RRI is again very strong. In the euro area, the predictive ability of the three-month RRI (three-month tenor) is considerable, with adjusted R^2 values equal to 84 percent and 80 percent for the two- and four-quarter horizons. The adjusted R^2 values are below 63 percent for the credit spreads.

For the two- and four-quarter horizons, the three-month RRI (one-month tenor) produces adjusted R^2 values equal to 82 percent and 70 percent for the United States. The performance is lower for credit risk indicators. The GZ spread and the CDS spread generate R^2 values that are 15 and 20 percentage points below the R^2 values of the RRI, respectively.

In summary, these results indicate that the expected bank RRI brings additional information that helps predict real activity in the euro area and the United States. In general, the tenor of the RRI is longer for the euro area than for the United States (three months versus one month). This result is probably partly driven by the way expectations are formed in the two areas. In particular, the dynamics of the monetary policy in the euro area during the sovereign debt crisis may have affected the expectations process.

3.4 Predicting Bank Lending

Tables 3 and 4 present the results of the predictive regressions for bank lending in the euro area and the United States, respectively. We investigated several specifications of the RRI and found that predicting lending relies on relatively long expectations. In the euro area, the best predictions are obtained with the 3-month RRI for the two-quarter horizon and the 12-month RRI for the four-quarter horizon. The adjusted R^2 is as high as 84 percent for both horizons. Credit spreads also perform well, with adjusted R^2 values close to 80 percent.

In the United States, predictions are often improved when we consider a more distant starting date (such as the 12-month RRI) and a longer tenor (such as 6 months). We note that, in general, R^2 values are relatively high because of the persistence in the predicted variable. The 12-month RRI (with a 6-month tenor) has by the highest predictive ability for bank lending. The adjusted R^2 is as high as 49 percent and 79 percent for the two- and four-quarter horizons. In comparison, credit spreads generate R^2 values close to 40–60 percent for these horizons.

We now decompose bank lending into its main components: consumer loans, real estate loans, and commercial and industrial loans. For the euro area, the three-month RRI produces the best performance for consumer loans, real estate loans, and commercial and industrial loans, although predictions provided by the GM spread are in general in a similar range of values. In all cases, the adjusted R^2 values obtained with the RRI are remarkably high, between 65 percent and 80 percent. For commercial and industrial loans, the GM spread is still slightly dominated by the RRI.

In the United States, we find that spread indicators usually exhibit good predictive performance. For consumer loans, the adjusted R^2 is the highest for the GZ spread. For real estate loans, the 12-month RRI has the highest performance. For commercial and industrial loans, the GZ spread again dominates. For the RRI, the adjusted R^2 values are close to 80 percent for the two-quarter horizon and 75 percent for the four-quarter horizon. It is remarkable that RRIs and the GZ indicators have similar predictive ability, despite being built on different types of information.

In summary, (i) real activity variables rely on relatively short expectations, so short-horizon RRIs perform quite well, while CDS and GZ/GM spreads usually fail at predicting real activity; (ii) bank lending variables rely on relatively long expectations, so long-horizon RRIs perform better in the United States. The main advantage of the RRIs is that they allow us to adapt the predictor to the length of the expectations needed. Short horizons (typically the 3-month RRI) are sufficient for real activity variables; long horizons (typically the 12-month RRI) are useful for bank lending variables.

4. Rollover Risk Indicator and Liquidity Regimes

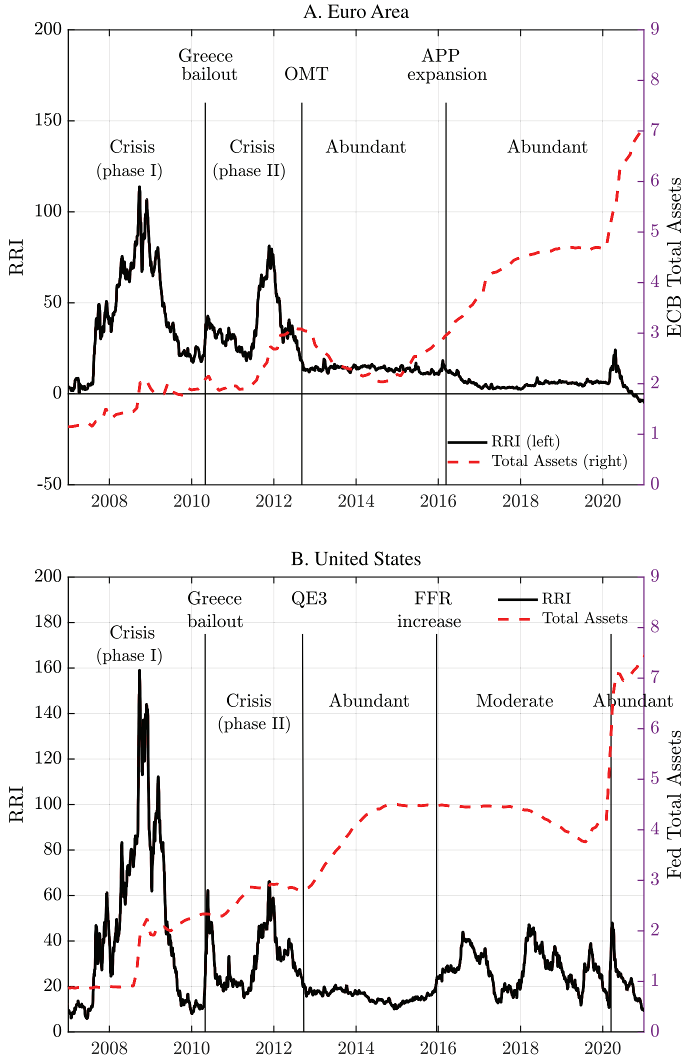
The evolution of the rollover risk indicator helps to contrast three liquidity regimes for central banks: (i) a *crisis* regime, associated with a lack of liquidity in the financial system and a strong connection between liquidity risk and credit risk, (ii) a regime of *abundant liquidity*, associated with massive central bank injections of liquidity, flat forward funding spreads, and a disconnect between liquidity and credit risk, and (iii) a regime of *moderate liquidity*, characterized by uncertainty over the cost of liquidity that is however unrelated to credit risk. Figure 2 displays the three-month RRI and the size of the central bank balance sheet, for the euro area and the United States, respectively. The latter provides an indication of changes in the supply of central bank liquidity. To cross-check what the RRI reveals about liquidity regimes, the CDS spread (as an indicator of banks' credit risk) and the uncertainty over short-term interest rates (measured as the sum of disagreement among forecasters and the perceived variability of future aggregate shocks; see Istrefi and Mouabbi 2018) are displayed in Figure 3. In addition, Figures 4 and 5 provide more detailed dynamics of the RRI for the euro area and the United States, respectively.

4.1 The Euro Area

4.1.1 Crisis Regime—Phase I: The Interbank Crisis (Summer 2007–May 2010)

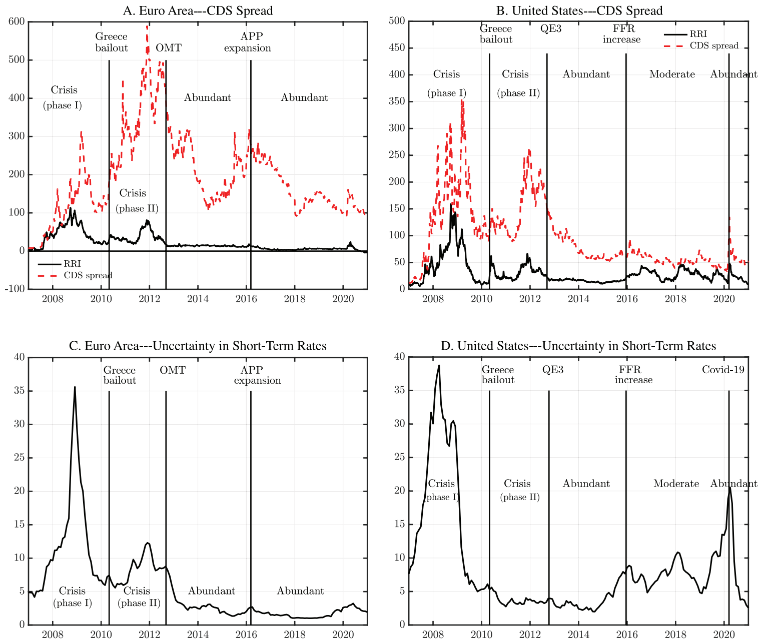
The RRI was negligible, below 5 bp, until mid-2007 (panel A of Figure 4). In the fall of 2007, the RRI increased to approximately 50 bp. In September 2008, it jumped again, although it did not exceed 120 bp.

Figure 2. Rollover Risk Indicator and Central Bank's Total Assets



Note: Panel A displays the three-month rollover risk indicator (in bp) and the ECB total assets (in EUR trillion). Panel B displays the three-month rollover risk indicator (in bp) and the Federal Reserve total assets (in USD trillion). The RRI series are smoothed using a five-day moving average. The sample periods run from January 2005 to December 2020.

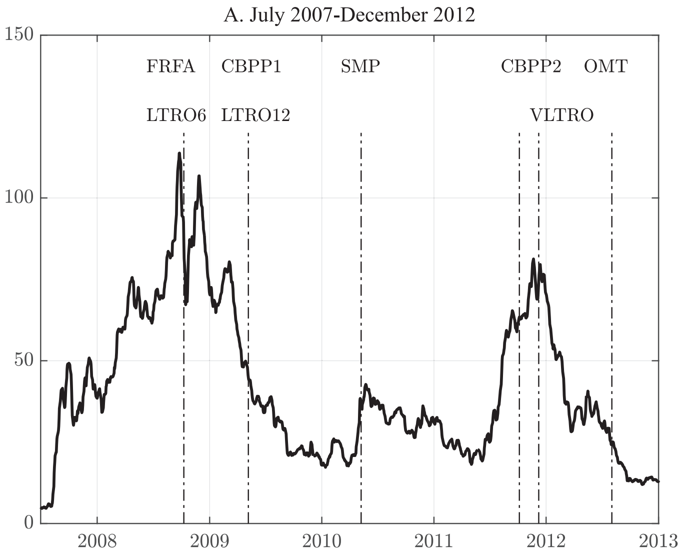
Figure 3. Bank CDS Spreads and Uncertainty in Short-Term Interest Rates

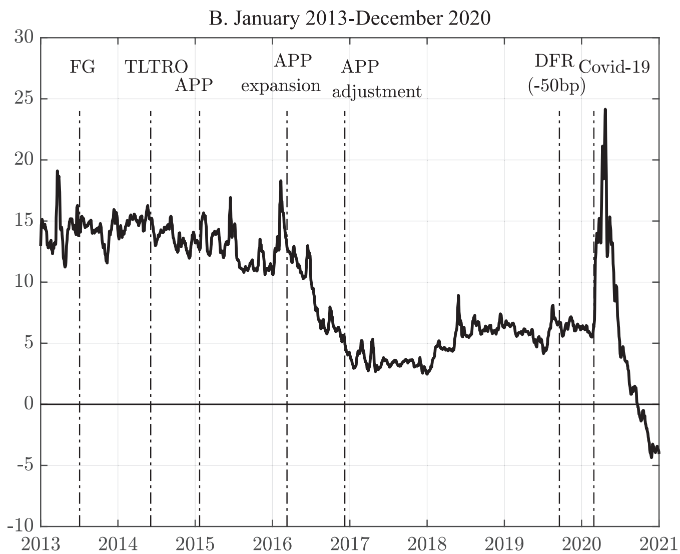


Note: Panels A and B display the bank CDS spread and the rollover risk indicator ($RRI^{(3m)}_{(3m,3m)}$) (in bp) for the euro area and the United States, respectively. The RRI and credit spread series are smoothed using a five-day moving average. Panels C and D display the uncertainty in three-month interest rates in three months, as measured as the sum of disagreement among forecasters and the perceived variability of future aggregate shocks for the euro area and the United States, respectively. See Istrefi and Mouabbi (2018). The sample periods run from January 2007 to December 2020.

We observe that (i) the ECB took measures at a time when bank rollover costs were high and (ii) their effects were quite immediate. The ECB's reaction was first to carry out its main refinancing operations through a fixed-rate tender procedure with full allotment (FRFA) in October 2008, so that all demand for liquidity would be satisfied as long as adequate collateral was available. The introduction of the FRFA credit operations built up excess liquidity in the banking system. The RRI almost instantaneously fell in reaction to this measure. In a second round, the ECB sought to satisfy

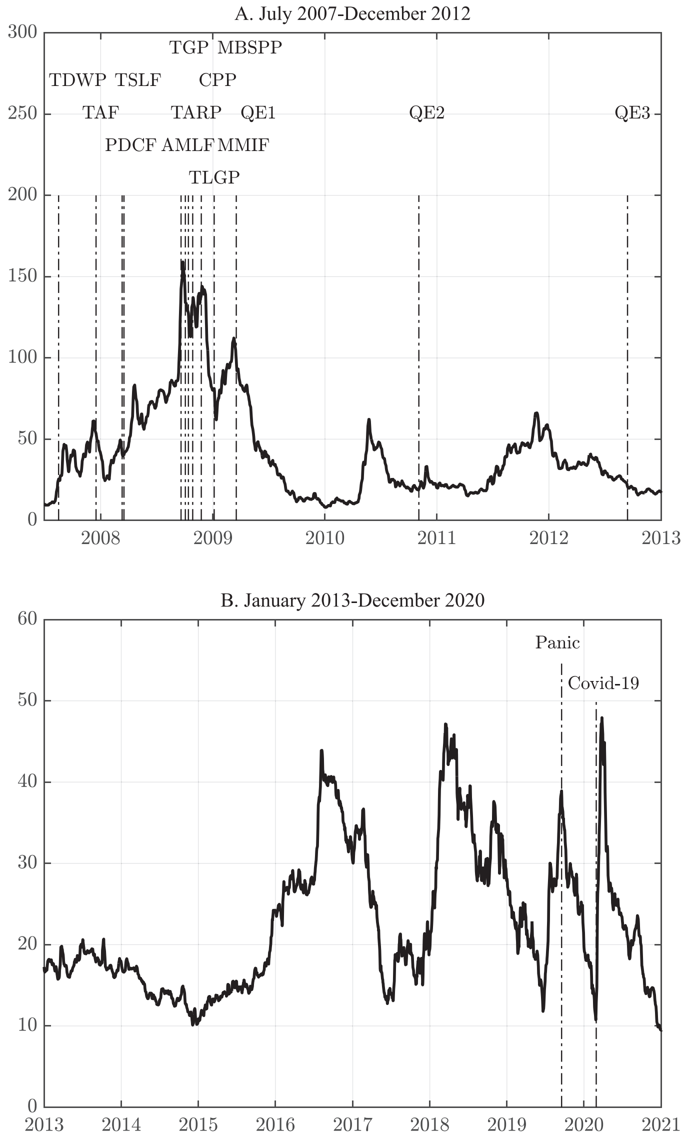
Figure 4. Rollover Risk Indicator for the Euro Area—Subsamples





Note: The figure displays the rollover risk indicator ($RRI^{(3m)}_{(3m,3m)}$) (in bp) for the euro area for two subsamples. The series are smoothed using a five-day moving average.

Figure 5. Rollover Risk Indicator for the United States—Subsamples



Note: The figure displays the rollover risk indicator ($RRI^{(3m)}_{(3m,3m)}$) (in bp) for the euro area for two subsamples. The series are smoothed using a five-day moving average.

the increased demand for liquidity by adjusting both the timing and the maturity of open market operations: 3- and 6-month full allotment long-term refinancing operations (LTROs) were implemented in November 2008 (EUR 300 billion) plus 12-month LTROs in June 2009 (EUR 442 billion). Providing banks with large amounts of liquidity for one year at a favorable rate allowed them to build up liquidity buffers. The combination of these unconventional responses had a beneficial impact on rollover risk, as the RRI decreased to 60 bp at the beginning of 2009.

This suggests that extended-maturity LTROs are an efficient tool to reduce bank borrowing costs by limiting rollover risk on maturing debt. By increasing the duration of their refinancing operations, the ECB reduces the credit risk premium of troubled banks by relaxing the constraint of bank equity holders associated with the frequently accruing rollover costs (Nyborg 2017).

4.1.2 Crisis Regime—Phase II: The Sovereign Debt Crisis (2010–12)

In reaction to the sovereign debt crisis, the ECB expanded its monetary outright portfolio in May 2010 through secondary market purchases of sovereign bonds under a new Securities Markets Program (SMP). The SMP was effective at mitigating upward pressures on the interbank market: the RRI remained relatively low, close to 20 bp, suggesting that there was no lack of liquidity in the euro market at that time (panel A of Figure 4). However, this program did not stop the rise in sovereign spreads. By July 2011, when markets started to question the status of Italian and Spanish sovereign debts, financial tensions intensified again and the crisis turned into a twin sovereign debt and banking crisis. Concerns about the solvency of large European banks increased, as testified by the jump in banks' CDS spreads in the second half of 2011. In August 2011, the RRI increased in parallel, from 25 to 60 bp at the end of the month, and then stabilized.

At the end of 2011, the ECB intervened substantially, using several measures designed to address funding risk: two LTROs of 12 and 13 months announced on October 2011, the second Covered Bond Purchase Program (CBPP2), and the announcement in December 2011 of two 36-month very long-term refinancing operations (VLTROs) to give banks funding certainty and help them sustain credit lines to the private sector. The ECB's balance sheet thus increased from approximately EUR 2 trillion in mid-2011 to almost EUR 3 trillion in mid-2012. The new sets of LTROs, by providing full-allotment liquidity and financing at a fixed policy rate and at a longer maturity, served as indirect bailout for weaker banks and sovereigns in the euro area. In this context, many euro-area banks have converted most of their short-term secured funding into long-term debt, by using swap operations. VLTROs induced an increase in the overall maturity of banks' liabilities, reducing their maturity mismatch and ultimately their rollover risk. Consequently, the RRI started to fall as soon as the monetary policy measures were announced, and it reached a first plateau at 30 bp in April despite still-elevated bank CDS rates.[16]

The speech by Mario Draghi on July 26, 2012, in which he stated that the ECB was ready to do "whatever it takes to preserve the euro" and the announcement shortly after of the Outright Monetary Transactions (OMT) program (with the option for governments to request the purchase of short-term sovereign bonds in secondary markets in unlimited amounts, under strict conditions) put the ECB in the position of lender of last resort for sovereigns. In turn, the rollover risk of banks stabilized: by end-2012, the RRI was close to 15 bp.

4.1.3 Abundant Liquidity (2013–February 2020)

After the OMT announcement, the euro area entered a persistent regime with very little uncertainty over the expected funding cost of banks. Remarkably, liquidity risk was low but the CDS spreads were still high. However, the combined effects of the FRFA of the ECB and the off-balance-sheet option character of the OMT kept the RRI flat at a low level (panel B of Figure 4).

[16] A substantial literature has evaluated these measures, in most cases finding that the programs worked as intended. For instance, Pelizzon et al. (2016) show that LTROs weakened the sensitivity to the credit risk of market-makers' liquidity provision, highlighting the importance of funding liquidity measures as determinants of market liquidity. Carpinelli and Crosignani (2017) show that banks more affected by the liquidity drought used central bank liquidity to restore credit supply, while less-affected banks increased their holdings of high-yield government bonds.

Given the low inflation and the persistence of low real growth in the area, the ECB adopted additional conventional and unconventional measures. The deposit facility rate was put into negative territory in June 2014, and the Asset Purchase Program (APP) was launched in 2015 (EUR 60 billion per month). In March 2016, the ECB took several measures to add further monetary stimulus (Hartmann and Smets 2018): The APP was expanded to EUR 80 billion in monthly purchases, a Corporate Sector Purchase Program (CSPP) was launched, and Targeted Longer-Term Refinancing Operations (TLTRO-II) were announced with a maturity of four years. This new package of measures allowed funding spreads to decrease considerably. The RRI declined from an already low 15 bp to 5 bp.

The liquidity injected into the financial system increased rapidly by EUR 2.5 trillion between 2015 and 2019, and the interest rate uncertainty fell below 2 percent, notably under the influence of the commitment to the future path of interest rates (forward guidance) implemented from July 2013.

4.2 The United States

4.2.1 Crisis Regime—Phase I: The U.S. Financial Crisis (Summer 2007–May 2010)

The first signs of stress on interbank liquidity appeared in the summer of 2007 with an increase in the RRI to approximately 50 bp (see panel A of Figure 5). The Federal Reserve introduced the Term Discount Window Program (TDWP) in August 2007, a temporary program that offered discount window funds with maturities beyond overnight and created the Term Auction Facility (TAF) in December 2007. As argued by Berger et al. (2014), these facilities increased aggregate lending, enhancing lending by expanding banks and slowing the decline in credit supplied by contracting banks.

However, these measures were not sufficient in view of the severity of the crisis. The usual redistribution mechanisms for liquidity within the financial system were too much altered. By mid-September 2008, the RRI jumped to a level close to 150 bp. The Federal Reserve started to provide liquidity directly to market participants through several programs and facilities: the Temporary Guarantee Program for money market funds (TGP) and the

Asset-Backed Commercial Paper and Money Market Liquidity Facility (AMLF) in September 2008; the Troubled Asset Relief Program (TARP) and the Capital Purchase Program (CPP), which were intended to provide capital injections for financial institutions in October 2008; the Money Market Investor Funding Facility (MMIFF) and the Term Asset-Backed Securities Loan Facility (TALF) in November 2008. In March 2009, the Federal Reserve decided to purchase up to USD 300 billion of longer-term Treasury securities (a program called quantitative easing, QE1) and to increase the purchase of agency debt.

Overall, the Federal Reserve injected approximately USD 1.3 trillion in liquidity between the summer of 2007 and the end of QE1 in May 2010. All these monetary policy actions seem to have dramatically reduced the cost of bank rollover: in early 2010, the RRI returned to its pre-crisis levels (approximately 10 bp).

4.2.2 Crisis Regime—Phase II: Between QE2 and QE3 (2010–12)

The period 2010–12 corresponds to the sovereign debt crisis in the euro area. The global integration of liquidity markets for large banks was clearly manifested during the second phase of the crisis. The Merkel-Sarkozy decision in October 2010 to impose losses on the private-sector lenders to the Greek Republic perturbed money markets in both euros and dollars. U.S. banks and money market funds held large positions in securities issued by European banks or had direct exposure to banks with direct exposure to Europe.

Financial tensions started to increase in spring 2010, as market participants started to question whether Greece, and possibly other highly indebted European countries, would be pushed to default and perhaps out of the euro area. The RRI increased by 20 bp (see panel A of Figure 5). The Federal Reserve started a second round of quantitative easing (QE2) in November 2010, buying USD 580 billion of Treasury securities by July 2011. Both spreads decreased to a level close to 20 bp, suggesting that liquidity was sufficiently abundant in the U.S. market. However, after stopping QE2 and facing a broadening of the sovereign debt crisis to Italian and Spanish sovereign debt, the RRI increased to 35 bp, suggesting that market participants expected the stress on money markets to resume.

4.2.3 Abundant Liquidity during QE3 (2013–15)

In September 2012, the Federal Reserve decided to launch an open-ended bond-purchasing program for agency mortgage-backed securities (QE3). The period of this program was characterized by additional increases in the supply of liquidity by the Federal Reserve. As shown in panel B of Figure 2, the Federal Reserve's balance sheet increased by USD 1.7 trillion to reach approximately 4.5 trillion in December 2015, a level five times larger than that before the crisis. The RRI stabilized at approximately 25 bp. A highly likely consequence of this larger scale of excess liquidity was that the rollover costs of large U.S. banks (panel B of Figure 5) were flat. During this period, bank CDS spreads decreased from above 150 bp to 60 bp and short-term interest rate uncertainty was extremely low (below 5 percent). Interestingly, the taper tantrum that hit global financial markets in Q2 and Q3 of 2013 had no effect on the expected cost of bank rollover.

In October 2014, the Federal Reserve announced the end of large-scale asset purchases. With QE ending, the Federal Reserve laid out its exit strategy: monetary policy normalization would consist of gradually raising its target range for the federal funds rate to more normal levels and gradually reducing the Federal Reserve's securities holdings. In reaction, the uncertainty associated with the interest rate increased.

4.2.4 Normalization of Federal Reserve Monetary Policy (2016–October 2019)

In December 2015, the Federal Reserve raised the target range for the federal funds rate for the first time since December 2008, and continued to increase it until January 2019 (panel B of Figure 5). It also began to gradually reduce its securities holdings from January 2018. The Federal Reserve's balance sheet was reduced to a level of USD 3.8 trillion in the summer of 2019 (panel B of Figure 2).

On September 16, 2019, there was an incident on the interbank market: the market rate spiked because cash-rich banks preferred keeping excess liquidity on their books to lending on the market to smooth a short episode of higher demand from other market players.

The Federal Reserve had to inject a massive amount of liquidity (over USD 50 billion) into the repo market the next day. The RRI had been rising in the few days before the panic. It almost instantaneously reverted on September 17 to a declining trend, suggesting that the event was due to a purely temporary lack of liquidity. Within a week after the incident, the Federal Reserve stepped up its liquidity supply to offer at least USD 75 billion in overnight repo funding and between 135 and 170 billion in term funding. Furthermore, additional monthly purchases of up to USD 60 billion of Treasury bills were announced, increasing its balance sheet again.

4.3 The COVID-19 Pandemic

The World Health Organization raised the risk of COVID-19 going global from high to very high on February 28, 2020. By that time, the United States was in a regime of moderate liquidity while the euro area was in a regime of abundant liquidity. Given these initial conditions, the pandemic could be expected to hit the bank RRI in very different proportions on the two sides of the Atlantic. And this is what happened (see panels B in Figures 4 and 5).

In the euro area, the spike in the RRI has been moderate, reaching approximately 24 bp as of end of April, before falling back to 0 bp in September 2020. In the United States, the RRI jumped to 50 bp. In addition, the rise in the RRI has been correlated with those of measures of bank credit risk (spreads on bank corporate bonds and CDSs on bank debt), a worrying feature already observed during the crisis environment that characterized U.S. money markets between 2007 and the beginning of QE3 in September 2012.

The ECB expanded its provision of liquidity in quantity and through various channels. The March 18 and April 30, 2020 announcements by the ECB of (i) a new temporary Pandemic Emergency Purchase Program (PEPP) that will have an additional envelope of EUR 750 billion until the end of 2020 and (ii) a new series of seven additional longer-term refinancing operations, called pandemic emergency longer-term refinancing operations (PELTROs) confirms (i) the continuation of the abundant regime and (ii) the desire of lengthening bank debt maturity and reducing rollover risk. In addition, the ECB decided to increase the initial EUR 750 billion envelope for the PEPP by EUR 600 billion on June 4, 2020 and by EUR

500 billion on December 10, 2020 for a new total of EUR 1,850 billion.

The Federal Reserve responded swiftly too. It announced several extraordinary measures to increase liquidity on U.S. money markets between March 12 and April 9, 2020 including (i) an injection of up to USD 1.5 trillion in the repo market; (ii) the purchase of at least USD 500 billion of Treasury securities and at least USD 200 billion of mortgage-backed securities; (iii) encouraging banks to use the discount window and intraday credit from the Federal Reserve; (iv) the establishment of the Primary Dealer Credit Facility (PDCF), the Commercial Paper Funding Facility (CPFF), and the Money Market Mutual Fund Liquidity Facility (MMFLF). Beyond the size of these operations, the Federal Reserve has made liquidity available through differentiated instruments to target various forms of funding stress.[17]

These multiple measures provided the U.S. money market with abundant liquidity conditions, and the RRI fell sharply to reach 25 bp at the end of May 2020 and 10 bp in December 2020. To some extent, this multiplicity of support channels echoes the ECB experience. In periods of stress, it is important to combine a large envelope of excess liquidity and multiple channels that target market participants confronted with specific forms of liquidity shortage.

4.4 Statistical Approach

We complement the narrative approach with a statistical approach based on a simple Markov-switching model. The objective is to estimate a model with regime-dependent means and volatilities and analyze whether the detected regimes do correspond to our narrative. The RRI is assumed to be driven by the following process:

$$RRI_{t+1} = \mu(\mathcal{S}_{t+1}) + \varepsilon_{t+1}, \tag{3}$$

where $\mu(\mathcal{S}_{t+1})$ is the vector of expected returns, conditional on state $\mathcal{S}_{t+1}$. The vector of unexpected returns is defined as

[17] See, among others, Gilchrist et al. (2020), Falato, Goldstein, and Hortaçsu (2021), Haddad, Moreira, and Muir (2021), and Chodorow-Reich et al. (2022) for analysis about the effects of Federal Reserve actions on markets and the economy in 2020.

$\varepsilon_{t+1} = \sigma(\mathcal{S}_{t+1})z_{t+1}$, where $\sigma(\mathcal{S}_{t+1})$ denotes the volatility of unexpected returns and z_{t+1} is a sequence of iid innovations with distribution $N(0,1)$.

States are defined by the Markov chain $\{\mathcal{S}_t\}$ with k regimes and transition matrix

$$P = \begin{pmatrix} p_{11} & \cdots & p_{1k} \\ \vdots & \ddots & \vdots \\ p_{k1} & \cdots & p_{kk} \end{pmatrix},$$

where the transition probabilities are $p_{ij} = \Pr(\mathcal{S}_t = j|\mathcal{S}_{t-1} = i)$, $i,j \in \{1,\ldots,k\}$. We assume that expected returns $\mu(\mathcal{S}_{t+1}) = \mu_{(k)}$ and volatility $\sigma(\mathcal{S}_{t+1}) = \sigma_{(k)}$ are constant within states if $\mathcal{S}_{t+1} = k$.

We estimate a three-state model using standard likelihood maximization over the period from January 2007 to December 2020.[18] Table 5 reports the parameter estimates. In the euro area, the RRI varies between the high regime ($\mu_{(3)} = 68$ bp, $\sigma_{(3)} = 2.3$) and the intermediate regime ($\mu_{(2)} = 30$ bp, $\sigma_{(2)} = 0.53$) until September 2012. As for the United States, the high regime corresponds to the periods from February 2008 to May 2009 and from August 2011 to February 2012. After 2012, the RRI remains in the low regime ($\mu_{(1)} = 9$ bp, $\sigma_{(1)} = 0.25$) until the end of the sample, with an exception in April 2020 during the COVID-19 pandemic. Figure 6 shows the evolution of the expected levels across regimes.

For the United States, we observe a sequence of regime switches, from the high RRI regime ($\mu_{(3)} = 83$ bp, $\sigma_{(3)} = 7.8$) to the low RRI regime ($\mu_{(1)} = 16$ bp, $\sigma_{(1)} = 0.15$), reflecting the hectic evolution of market rates during this period. The high regime occurs from April 2008 to May 2009 (subprime crisis) and again from November to December 2011 (sovereign debt crisis). Then, there is one clear detection of the low RRI regime corresponding to period from September 2012 to December 2015, with an average RRI equal to 16 bp. From December 2015 onward, we observe that the RRI is mainly in the intermediate regime ($\mu_{(2)} = 33$ bp, $\sigma_{(2)} = 0.55$), which corresponds to our moderate liquidity regime.

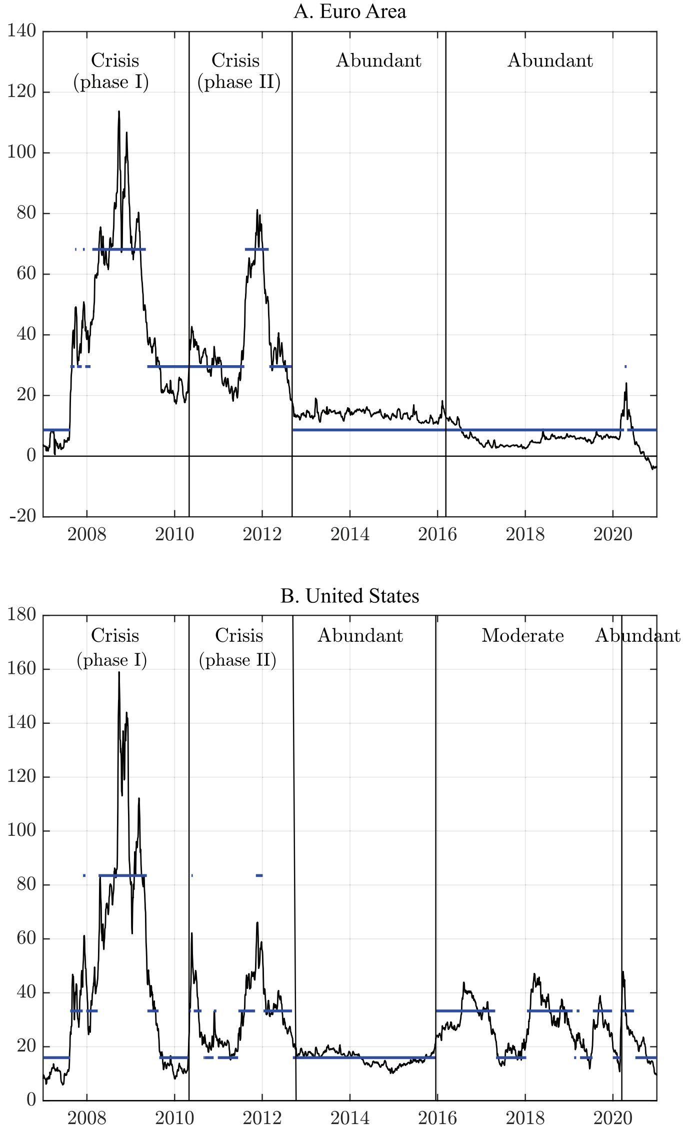
[18]A likelihood-ratio test indicates that the two-state version is rejected under the null hypothesis.

Table 5. Parameter Estimates of a Three-Regime Markov-Switching Model for the RRI

	Euro Area			United States		
	Regime 1	**Regime 2**	**Regime 3**	**Regime 1**	**Regime 2**	**Regime 3**
$\mu_{(k)}$	8.647	29.539	68.185	15.945	33.273	83.492
	(0.104)	(0.318)	(0.857)	(0.100)	(0.217)	(1.532)
$\sigma_{(k)}$	0.246	0.532	2.310	0.153	0.548	7.754
	(0.007)	(0.034)	(0.166)	(0.005)	(0.022)	(0.577)
Transition Matrix						
$P_{1;:}$	0.999	0.003	0.000	0.995	0.007	0.000
$P_{2;:}$	0.001	0.993	0.008	0.005	0.991	0.011
$P_{3;:}$	0.000	0.005	0.992	0.000	0.003	0.989
Log-Likelihood	4,846.3			4,897.6		

Note: Standard errors are in parentheses. The sample period runs from January 2007 to December 2020.

Figure 6. Liquidity Regimes



Note: Panels A and B display the narrative liquidity regimes together with statistical regimes obtained from a Markov-switching model of rollover risk indicator for the euro area and the United States, respectively. The series are smoothed using a five-day moving average. The sample periods run from January 2007 to December 2020.

In summary, these results confirm some correspondence between the narrative liquidity regimes and the statistical regimes based solely on the dynamic behavior of the RRI.

5. Conclusion

In this paper, we build a new indicator of bank rollover risk (RRI) using daily data from euro and dollar interest rates of various maturities. It captures the market expectations of future funding cost and is constructed such that the underlying tenors are consistent with the maturity of the interest rate contracts. This property is crucial because different frequencies of payments imply different underlying rollover risks. Another advantage of RRIs is that they can easily be measured at a daily frequency and therefore are well suited for real-time analyses.

We provide evidence that rollover risk is an important driver of both real activity and bank lending. It suggests that there is room for monetary authorities in a financial crisis mainly driven by liquidity drying. Providing public liquidity to financial institutions can help mitigate the lack of private liquidity and the subsequent increase in funding cost. In this perspective, the quantitative easing implemented in the United States and the euro area have helped reduce the impact of the financial crisis on the real side of the economy.

Our indicator provides central banks with an indication of the market perception of bank funding stress. In crisis times, lower levels of our indicator than the spot BOR-OIS spread point to market participants expecting that funding stress will be temporary. However, increases in the RRI are particularly useful indicators for central banks and market participants because they point to funding stress that may persist. Finally, our indicators help characterize liquidity regimes (crisis, moderate, and abundant) that reflect the levels of liquidity supplied by either the ECB or the Federal Reserve. We show in particular how liquidity regimes help explain why the COVID-19 pandemic had a much larger impact on U.S. funding conditions than on euro-area ones.

Appendix A. Methodology for Constructing Yield Curves

This appendix provides a description of the instruments used for the construction of yield curves and results on the quality of the fit. We define two types of yield curves. The discounting curve corresponds to the OIS curve with overnight rates. The forwarding curves correspond to yield curves with tenors 1 month, 3 months, 6 months, and 12 months. We denote by x the tenor of a given curve.

A.1 Notations

We define $P_x(t,T)$, $t \leq T$, the discount factor, i.e., the price of a zero-coupon bond at time t for maturity T, for underlying rate tenor x, with $P_x(t,t) = 1$ and t is the reference date. The simply compounded zero-coupon rate at date t for maturity T, denoted by $Z_x(t,T)$, is defined from

$$P_x(t,T) = \frac{1}{[1 + Z_x(t,T)]^{\tau_x(t,T)}},$$

where $\tau_x(t,T)$ is the year fraction for interval $[t,T]$ under the convention of curve x. For zero-coupon rates, the time interval is computed as $\tau_x(t,T) = (T-t)/365$.

We define the simply compounded forward rate at date t for the future time interval $[T_{k-1}, T_k]$, with tenor x, as

$$\tilde{F}_{x,k}(t) \equiv \tilde{F}_x(t, T_{k-1}, T_k) = \frac{1}{\tau_{x,k}} \left[\frac{P_x(t,T_k)}{P_x(t,T_{k-1})} - 1 \right],$$

where $\tau_{x,k}$ is the year fraction for interval $[T_{k-1}, T_k]$ under the convention of curve x. For forward rates, the time interval is computed as $\tau_{x,k} = (T_k - T_{k-1})/360$ (actual/360). For example, $\tilde{F}_{3\text{m},6\text{m}}(t)$ denotes the forward rate with tenor three months between $t + 3\text{m}$ and $t + 6\text{m}$.

In the multicurve environment, the following no arbitrage relation holds:

$$P_x(t,T_k) = P_x(t,T_{k-1}) P_x(t,T_{k-1},T_k), \quad t \leq T_{k-1} \leq T_k,$$

where $P_x(t, T_{k-1}, T_k)$ is the forward discount factor at date t and corresponding to the future time interval $[T_{k-1}, T_k]$, with

$$P_x(t, T_{k-1}, T_k) = \frac{P_x(t, T_k)}{P_x(t, T_{k-1})} = \frac{1}{1 + \tilde{F}_{x,k}(t)\tau_{x,k}}.$$

We typically consider constant time intervals such as $T_k - T_{k-1} = \delta$. The yield curve of the δ-month forward rates is denoted by $\mathcal{C}_x^{(F)} = \left\{T \rightarrow \tilde{F}_x(t, T, T+\delta), t \geq T\right\}$.

A.2 Interbank Market Instruments

A.2.1 Overnight Index Swap (OIS)

The reference rate for overnight over-the-counter (OTC) transactions is the federal funds rate in the United States and the EONIA (euro overnight index average) rate in the euro area. An OIS is an interest rate agreement that involves the exchange of the overnight rate and a fixed interest rate. The floating rate is determined by the geometric average of the overnight index rate over the time interval of the contract period. The fixed leg is quoted in the market as a yield that is applied over the duration of the swap. The two counterparties of an OIS contract agree to exchange at maturity the difference between interest accrued at the agreed fixed rate and the floating rate on the notional amount of the contract. No principal is exchanged at the beginning of the contract. For maturities up to one year, there are no intermediate interest payments. Then the broken period is at the beginning.

The floating rate is given by the formula

$$R_d(t, T_k) = \frac{360}{N_k}\left[\prod_{i=1}^{d_k}\left(1 + \frac{r_i n_i}{360}\right) - 1\right] \times 100,$$

where r_i is the overnight rate at date i, $N_k = T_k - t$ is the total number of days, d_k is the number of working days, and n_i is the number of days with rate r_i, with $N_k = \sum_{i=1}^{d_k} n_i$.

A.2.2 Deposit

Interbank deposits are OTC zero-coupon contracts that start at reference date t and cover the period $[t, T]$ with maturities T ranging from one day to one year. The London interbank offered rate (LIBOR) is the reference rate in the United States and the euro-area interbank offered rate (EURIBOR) is the reference rate in the euro area (IBOR, in short). They correspond to the rate at which interbank deposits are offered by a prime bank to another prime bank. Fixing rates are constructed as the trimmed average of the rates submitted by a panel of banks. The IBOR reflects the average cost of funding of banks on the interbank market for a given maturity. The deposit with duration x is selected for the construction of the curve with tenor x.

We denote by $R_x^D(t, T_k)$ the quoted rate (annual, simply compounded) associated with the deposit of maturity T_k, with tenor $x = T_k - t$ months. The implied discount factor at time t for time T_k is given by

$$P_x(t, T_k) = \frac{1}{1 + R_x^D(t, T_k)\tau_{x,x}}, \quad t \leq T_k.$$

A.2.3 Forward Rate Agreement (FRA)

FRA contracts are forward starting deposits. They are defined for forward start dates calculated with the same convention used for the deposits. Therefore, FRAs concatenate exactly with deposits. Market FRAs on x-tenor IBOR contracts can be selected for the construction of the short-term of the yield curve with tenor x.

We denote by $\tilde{F}_{x,k}(t)$ the forward rate reset at time T_{k-1}, with tenor $x = T_k - T_{k-1}$ months. Then the implied discount factor at time T_k is given by

$$P_x(t, T_k) = \frac{P_x(t, T_{k-1})}{1 + \tilde{F}_{x,k}(t)\tau_{x,k}}, \quad t \leq T_{k-1} \leq T_k.$$

A.2.4 Swap

Interest rate swaps are OTC contracts by which two counterparties exchange fixed against floating rate cash flows. On the U.S. market, the floating leg is usually indexed to the three-month LIBOR rate paid with three-month frequency. On the euro market, the floating leg is indexed to the six-month EURIBOR rate paid with six-month frequency. The day count convention (τ_S) is 30/360 (bond basis). Swaps on x-tenor IBOR contracts are selected for the construction of the medium and long term of the yield curve with tenor x.

A swap is defined by two date vectors $T = \{t, T_1, \cdots, T_n\}$ and $S = \{t, S_1, \cdots, S_m\}$ with $t < T_1 < S_1 < \cdots < T_n = S_m$ and $n < m$. The fixed leg pays a fixed rate at times S_j. The floating leg pays the IBOR with tenor $x = T_k - T_{k-1}$ fixed at time T_{k-1}. We denote by $S_x(t, T, S)$ the swap rate with floating leg payment dates T and fixed leg payment dates S, with tenor $x = T_k - T_{k-1}$ months. The price of a swap with payment times T and S is given by the no-arbitrage relation:

$$S_x(t, T, S) \sum_{j=1}^{n} P_d(t, S_j)\tau_j = \sum_{k=1}^{m} P_d(t, T_k)\tilde{F}_{x,k}(t)\tau_{x,k}.$$

Once the curve points at $\{t, T_1, \cdots, T_{k-1}\}$ and $\{t, S_1, \cdots, S_{j-1}\}$ are known, it is possible to bootstrap the yield curve at point $T_i = S_j$. In practice, the fixed leg frequency is annual, whereas the floating leg frequency is given by the IBOR tenor. Some points of the curve are unknown and have to be interpolated.

A.2.5 Basis Swap

Basis swaps are floating versus floating swaps, admitting underlying rates with different tenors. On the U.S. market, the typical basis swaps are 1-month versus 3-month, 3-month versus 6-month, and 3-month versus 12-month. On the euro market, the typical basis swaps are 1-month versus 3-month, 3-month versus 6-month, and 6-month versus 12-month. The quotation convention is to provide the difference (in basis points) between the fixed rate of the higher frequency swap and the fixed rate of the lower frequency swap. Basis swaps are used for the construction of the yield curve with non-quoted swaps (for instance, the six-month curve in the United States and the three-month curve in the euro area).

We define by $BS_{x,y}(t, T_x, T_y)$ the quoted basis spread for a basis swap receiving the long y-month rate and paying the short x-month rate plus the basis spread for maturity T_{m_x}. The price of a basis swap is given by the no-arbitrage relation:

$$\sum_{k=1}^{m_y} P_d(t, T_{y,k})\tilde{F}_{y,k}(t)\tau_{y,k}$$
$$= \sum_{j=1}^{m_x} P_d(t, T_{x,j})(\tilde{F}_{x,j}(t) + BS_{x,y}(t, T_x, T_y))\tau_{x,j}.$$

A.3 Construction of the Yield Curves

Two main approaches are usually adopted for fitting yield curves and extracting implicit forward rates. Central banks often construct smoothed Treasury yield curves following Nelson and Siegel (1987) or Söderlind and Svensson (1997) methodology. This parametric approach allows us to obtain a smoothed curve when the observed yields are relatively noisy, which is often the case of Treasury curves. In the case of FRA-swap rates, which usually display much smoother patterns, it is more common to use more direct bootstrapping techniques. In the baseline bootstrapping technique, one imposes the interpolated curve to pass through the observed sport rates. The resulting spot curve is rather smooth, but the forward curve often exhibits spikes. This is the reason why the objective function also imposes a smoothing of the forward rates. See Flavell (2010) at textbook level.

We briefly explain below how we construct the yield curve of a given tenor and compute tenor spreads. We consider a curve with a tenor x corresponding to overnight (the discounting curve), 1 month, 3 months, 6 months, and 12 months (the forwarding curves). All the curves are constructed using instruments with the tenor of the curve. The forwarding curves also depend on the OIS curve used for discounting future cash flows. Several techniques can be used for interpolating a yield curve. Usual techniques are the linear or cubic interpolations. These techniques can be applied to the discount factor, the log of the discount factor, or the zero-coupon rate. A feature of the multicurve environment is the scarcity of the data for a given curve (except for the discounting curve). This implies that a large amount of maturities must be interpolated. The selection of the interpolation technique is therefore critical.

Ideally, all the available discount factors should be exactly given by the interpolation, yielding an arbitrage-free curve. However, it would lead to a very erratic yield curve. To cope with this problem, we allow for some arbitrage opportunity to obtain a smooth curve. We minimize a weighted sum of the squared changes in the forward rates under the arbitrage-free restrictions and the squared difference between the market and theoretical prices. The criterion is based on the three-month forward rate. This maturity appears as a reasonable trade-off between the number of parameters to estimate and the ability to generate all the curves with similar data. For a given curve $\mathcal{C}_x^{(F)}$, we solve (imposing $T_k - T_{k-1} = 3\text{m}$ and $T_0 = t$):

$$\min_{\left\{\tilde{F}_x(t,T_{k-1},T_k)\right\}_{k=1}^N} w \sum_{k=1}^{N-1} \left(\tilde{F}_x(t,T_k,T_{k+1}) - \tilde{F}_x(t,T_{k-1},T_k)\right)^2 + (1-w) \sum_{j=1}^{n} \left(P_x^{mkt}(t,T_j) - P_x^{theo}(t,T_j)\right)^2,$$

where w is weight of the smoothness relative to the fit of the market prices (we use $w = 0.25$); $N = 120$ is the number of three-month forward rate over the 30 years used for the curve; n is the number of instruments used to construct curve with tenor x; $P_x^{mkt}(t,T_j)$ is the discount factor implied by the market quote, based on the pricing formula presented in Section A.2; $P_x^{theo}(t,T_j)$ is the discount factor implied by the estimated three-month forward rates:

$$P_x^{theo}(t,T_j) = \frac{P_x^{theo}(t,T_{j-1})}{1 + \tilde{F}_x(t,T_{j-1},T_j)\tau_{x,j}}, \qquad j = 1, \cdots, n,$$

with $P_x^{theo}(t,t) = 1$.

A.4 Evolution of the Rollover Risk Indicators

For the United States, the OIS, one-month, three-month, and six-month tenor curves are available on January 2005 up to 5 years, on July 2008 up to 10 years, and on September 2011 up to 30 years. For the euro area, the OIS, three-month, and six-month tenor curves are available on January 2005 up to 3 years, on April 2005 up to 7 years, on July 2005 up to 10 years, and on May 2008 up to

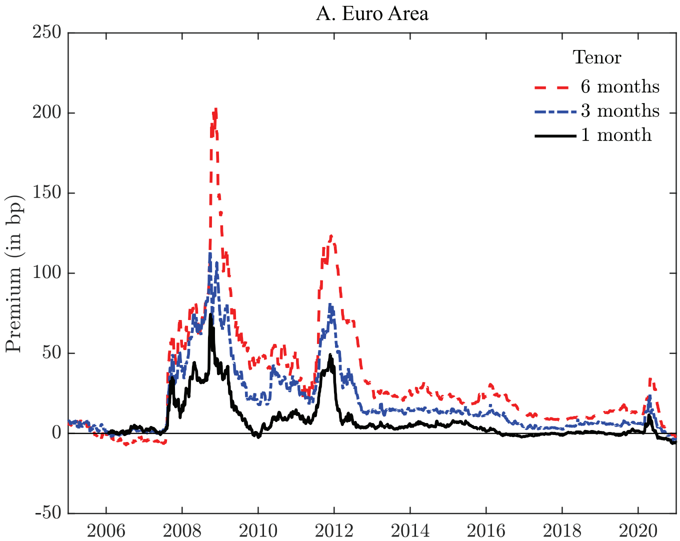
30 years. The one-month tenor curve is available on January 2006 up to 2 years, on May 2007 up to 3 years, and on June 2008 up to 30 years. Figure A.1 displays the time series of the forward funding spreads for the euro area and the United States for tenors of one, three, and six months. Before the start of the financial crisis in 2007, the difference between instruments with the same maturity but a different tenor was considered negligible. RRIs exploded in August 2007 and remain extremely high. They almost always increase with the tenor, although not linearly so. This result is illustrated by two episodes of particular interest in the euro area: during the 2007–09 crisis, RRIs were particularly high for the tenors of three and six months, with a spike above 100 bp for these spreads in January 2009. In contrast, during the sovereign debt crisis, RRIs increased in a more regular way. They increased up to 50, 75, and 120 bp for the one-, three-, and six-month tenors, respectively, in November 2011. In the United States, the financial crisis also generated substantial differences between tenors. The RRIs with a one-month tenor increased to 140 bp in January 2009, while RRIs with three- and six-month tenors jumped to 160 and 250 bp. Since the recent surge in spreads following the change in Federal Reserve interest rate policy (December 2015), we do not observe such large differences between tenors.

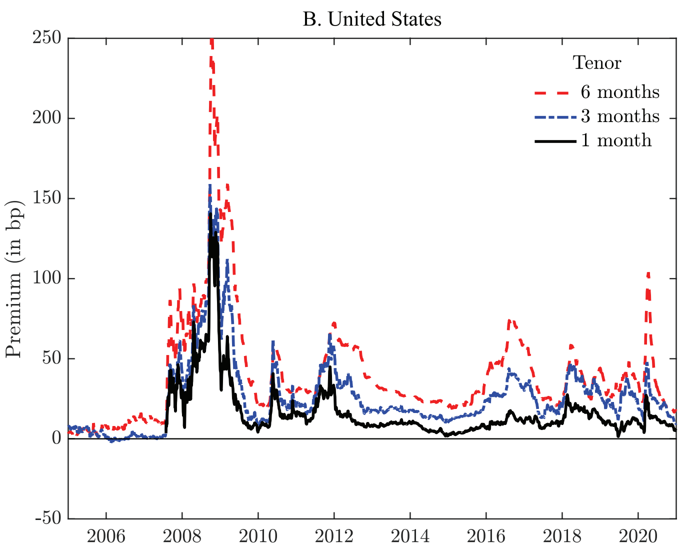
A.5 Goodness of Fit

Figure A.2 displays the evolution of the two components of the optimization criterion. In panel A, we report the relative error (in basis points) in the construction of the three-month and six-month curves for the euro area and the United States, which corresponds to the second term in the optimization criterion. Panel B corresponds to the volatility of the three-month forward rate (in basis points), which corresponds to the first term of the criterion. For both zones, the fit of the curve is very good (panel A).

For the euro area, the relative error is below 3 bp for the three-month curve and 1 bp for the six-month curve. After 2009, the relative error is much lower than 1 bp for both curves, with sample averages equal to 0.7 and 0.4 bp, respectively. In the United States, the relative error is always below 4 bp for the three-month curve and 2 bp for the six-month curve. After 2009, the relative error is

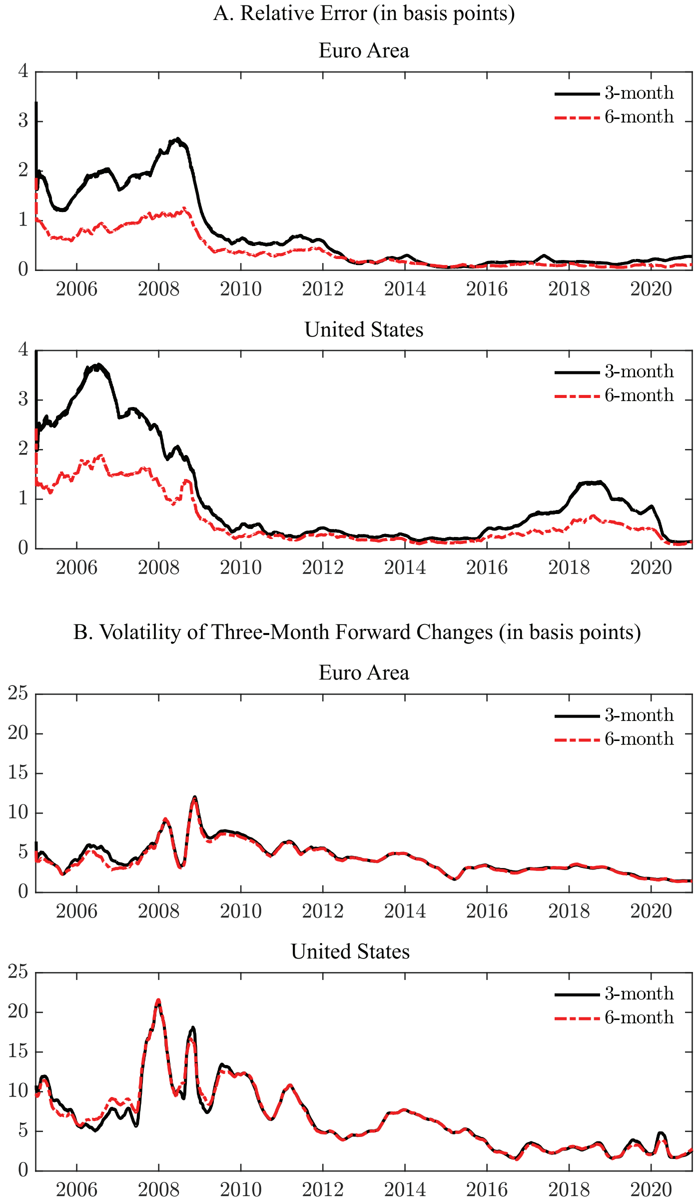
Figure A.1. Rollover Risk Indicators for the Euro Area and the United States





Note: Panel A displays the three-month rollover risk indicator for tenors one month, three months, and six months for the euro area. Panel B displays the three-month rollover risk indicator for tenors one month, three months, and six months for the United States. The series are smoothed using a five-day moving average. The sample periods run from January 2005 to December 2020.

Figure A.2. Relative Error in the Fit of Euro-Area and U.S. Curves



Note: Panel A displays the relative error (in basis points) in the construction of the three-month and six-month curves for the euro area and the United States. Panel B displays the volatility of the three-month forward rate (in basis points) for the construction of the three-month and six-month curves for the euro area and the United States. The series are smoothed using a five-day moving average. The sample periods run from January 2005 to December 2020.

usually below 1 bp for both curves, with sample averages equal to 1 and 0.5 bp, respectively.

On average, the relative error is equal to 0.71 bp and 1.05 bp for the three-month curve and 0.39 bp and 0.57 bp for the six-month curve in the euro area and the United States, respectively. In panel B, we also report the volatility of the three-month forward rate, which reflects the extend of the smoothing of the curves. As we note, in the euro area, the volatility rarely exceeds 10 bp. The volatility is higher in the United States (up to 20 bp in 2008 and usually below 10 bp after 2009). These results suggest that the fit of the three-month forward curve is well adjusted over our sample in both zones.

Appendix B. Predictive Content: Full Set of Results

This appendix reports the full set of results relative to the ability of our RRI to predict the evolution of indicators of real activity and bank lending.

Table B.1. Predicting Euro-Area Real Activity Variables

	3-Month RRI $\left(\boldsymbol{RRI}^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(\boldsymbol{RRI}^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
A. Real GDP Growth								
Variables in $t-1$								
r	0.139	0.141	0.129	0.136	0.155	0.111	–0.032	–0.083
(t-stat)	(3.510)	(3.953)	(3.067)	(3.248)	(3.984)	(3.184)	(0.805)	(1.231)
term	0.130	0.196	0.268	0.178	0.269	0.358	0.182	0.257
(t-stat)	(2.703)	(3.151)	(2.817)	(3.326)	(3.300)	(3.095)	(1.612)	(1.761)
Lag	0.183	0.188	0.063	0.034	0.177	0.188	0.583	0.372
(t-stat)	(1.007)	(1.184)	(0.353)	(0.153)	(1.072)	(1.223)	(3.411)	(2.281)
Variable	–3.806	–2.222	–1.676	–5.175	–2.860	–2.413	–0.173	–0.499
(t-stat)	(3.008)	(3.759)	(3.405)	(3.371)	(3.641)	(3.276)	(2.253)	(2.327)
Adj. R^2	0.596	0.615	0.683	0.663	0.619	0.632	0.385	0.462
Variables in $t-2$								
r	0.330	0.343	0.280	0.296	0.372	0.272	–0.021	–0.110
(t-stat)	(3.959)	(4.555)	(3.551)	(3.573)	(4.655)	(3.653)	(0.250)	(1.094)
term	0.320	0.471	0.563	0.401	0.636	0.815	0.525	0.613
(t-stat)	(2.576)	(3.793)	(2.812)	(3.093)	(4.053)	(3.543)	(1.517)	(1.714)
Lag	0.033	0.004	–0.003	–0.046	0.020	0.063	0.484	0.249
(t-stat)	(0.183)	(0.024)	(0.022)	(0.273)	(0.126)	(0.467)	(2.390)	(1.351)
Variable	–8.421	–5.109	–3.042	–9.949	–6.353	–5.067	–0.414	–1.007
(t-stat)	(4.027)	(5.061)	(6.188)	(5.745)	(5.261)	(4.614)	(2.029)	(2.865)
Adj. R^2	0.674	0.726	0.623	0.679	0.712	0.676	0.303	0.378

(*continued*)

Table B.1. (Continued)

	3-Month RRI $\left(\boldsymbol{RRI^{(xm)}_{3m,3m}}\right)$			12-Month RRI $\left(\boldsymbol{RRI^{(xm)}_{12m,12m}}\right)$				
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GM Spread**
Variables in $t-4$								
r	0.505	0.502	0.379	0.413	0.560	0.379	–0.233	–0.384
(t-stat)	(3.571)	(3.676)	(2.654)	(2.384)	(3.990)	(2.599)	(0.953)	(2.224)
term	0.504	0.708	0.827	0.597	1.011	1.320	1.006	1.021
(t-stat)	(1.944)	(2.782)	(1.990)	(2.010)	(3.346)	(3.168)	(1.217)	(1.360)
Lag	–0.116	–0.185	–0.224	–0.180	–0.174	–0.162	0.185	–0.073
(t-stat)	(0.966)	(1.514)	(2.158)	(1.505)	(1.430)	(1.529)	(0.886)	(0.494)
Variable	–14.994	–9.084	–5.341	–16.539	–11.330	–9.125	–1.016	–2.088
(t-stat)	(5.721)	(7.863)	(5.526)	(5.471)	(7.664)	(6.676)	(2.069)	(4.259)
Adj. R^2	0.658	0.703	0.555	0.605	0.683	0.619	0.150	0.268
B. Real Consumption Growth								
Variables in $t-1$								
r	0.081	0.087	0.068	0.069	0.094	0.066	–0.038	–0.043
(t-stat)	(3.437)	(3.851)	(2.785)	(2.642)	(4.156)	(2.916)	(1.310)	(1.566)
term	–0.031	0.005	0.031	–0.009	0.045	0.090	0.028	0.048
(t-stat)	(1.009)	(0.195)	(0.774)	(0.274)	(1.668)	(2.325)	(0.458)	(0.740)
Lag	0.013	–0.032	0.035	0.035	–0.028	0.006	0.390	0.222
(t-stat)	(0.053)	(0.147)	(0.169)	(0.146)	(0.127)	(0.030)	(1.602)	(0.880)
Variable	–2.017	–1.270	–0.723	–2.139	–1.599	–1.287	–0.125	–0.265
(t-stat)	(3.632)	(5.269)	(4.988)	(3.975)	(5.265)	(5.246)	(2.030)	(2.720)
Adj. R^2	0.489	0.538	0.491	0.464	0.534	0.520	0.313	0.364

(continued)

Table B.1. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
Variables in $t-2$								
r	0.126	0.138	0.101	0.102	0.147	0.107	–0.033	–0.012
(t-stat)	(2.866)	(2.843)	(2.143)	(1.993)	(3.090)	(2.308)	(0.580)	(0.189)
term	0.038	0.082	0.124	0.078	0.142	0.208	0.156	0.145
(t-stat)	(0.567)	(1.545)	(1.426)	(0.993)	(2.606)	(2.900)	(1.295)	(1.176)
Lag	0.358	0.288	0.423	0.434	0.299	0.341	0.695	0.624
(t-stat)	(2.256)	(2.230)	(3.558)	(3.155)	(2.485)	(3.280)	(4.159)	(3.313)
Variable	–2.874	–1.873	–0.883	–2.633	–2.319	–1.808	–0.171	–0.239
(t-stat)	(4.181)	(6.972)	(3.386)	(3.418)	(6.743)	(6.389)	(1.769)	(1.768)
Adj. R^2	0.680	0.714	0.634	0.630	0.705	0.684	0.572	0.556
Variables in $t-4$								
r	0.226	0.241	0.188	0.188	0.266	0.182	–0.112	–0.101
(t-stat)	(1.654)	(1.632)	(1.330)	(1.206)	(1.817)	(1.347)	(0.656)	(0.636)
term	–0.009	0.073	0.186	0.097	0.215	0.365	0.340	0.288
(t-stat)	(0.037)	(0.370)	(0.703)	(0.377)	(1.169)	(1.822)	(0.887)	(0.741)
Lag	0.103	0.028	0.125	0.177	0.043	0.062	0.497	0.322
(t-stat)	(0.530)	(0.146)	(0.662)	(0.887)	(0.229)	(0.331)	(1.798)	(1.074)
Variable	–6.633	–4.165	–2.167	–6.294	–5.186	–4.174	–0.414	–0.708
(t-stat)	(5.082)	(5.794)	(3.564)	(3.406)	(5.357)	(5.427)	(1.556)	(2.147)
Adj. R^2	0.545	0.586	0.464	0.458	0.576	0.542	0.313	0.311

(*continued*)

Table B.1. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			**12-Month RRI** $\left(RRI^{(xm)}_{12m,12m}\right)$				
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GM Spread**
C. Real Investment Growth								
Variables in $t-1$								
r	0.040	0.052	–0.018	–0.002	0.099	–0.065	–0.707	–0.878
(t-stat)	(0.176)	(0.253)	(0.095)	(0.008)	(0.494)	(0.330)	(1.970)	(2.315)
term	–0.346	–0.111	0.109	–0.179	0.150	0.460	–0.199	0.204
(t-stat)	(1.871)	(0.636)	(0.677)	(1.053)	(0.858)	(2.513)	(0.560)	(0.565)
Lag	–0.556	–0.571	–0.606	–0.601	–0.585	–0.583	–0.385	–0.506
(t-stat)	(3.802)	(3.917)	(4.272)	(4.313)	(4.016)	(3.861)	(1.631)	(2.847)
Variable	–13.452	–8.017	–5.422	–16.211	–10.297	–8.662	–0.850	–2.241
(t-stat)	(4.480)	(6.147)	(6.961)	(6.737)	(6.377)	(5.972)	(2.667)	(3.113)
Adj. R^2	0.419	0.442	0.486	0.467	0.447	0.448	0.128	0.301
Variables in $t-2$								
r	0.249	0.261	0.133	0.159	0.328	0.104	–0.601	–0.825
(t-stat)	(0.969)	(1.130)	(0.630)	(0.585)	(1.436)	(0.572)	(2.300)	(3.301)
term	0.059	0.364	0.622	0.240	0.745	1.201	0.665	0.885
(t-stat)	(0.189)	(1.467)	(1.670)	(0.799)	(2.653)	(3.208)	(0.846)	(1.173)
Lag	–0.010	–0.068	–0.082	–0.060	–0.062	–0.051	0.325	0.138
(t-stat)	(0.067)	(0.537)	(0.673)	(0.451)	(0.515)	(0.495)	(1.466)	(0.857)
Variable	–19.083	–11.877	–7.430	–22.151	–14.830	–12.354	–1.203	–2.721
(t-stat)	(4.777)	(7.231)	(8.585)	(7.214)	(7.833)	(7.378)	(2.728)	(4.194)
Adj. R^2	0.533	0.592	0.561	0.547	0.575	0.569	0.190	0.315

(continued)

Table B.1. (Continued)

Tenor x	**3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$ 1m**	**3m**	**6m**	**12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$ 1m**	**3m**	**6m**	**CDS Spread**	**GM Spread**
Variables in $t-4$								
r	0.222	0.172	–0.085	–0.009	0.295	–0.128	–1.585	–1.779
(t-stat)	(0.455)	(0.398)	(0.204)	(0.016)	(0.705)	(0.418)	(2.854)	(4.226)
term	0.144	0.489	0.855	0.316	1.167	1.967	1.784	1.673
(t-stat)	(0.186)	(0.784)	(0.836)	(0.379)	(1.730)	(2.251)	(0.858)	(0.888)
Lag	–0.069	–0.180	–0.194	–0.140	–0.191	–0.177	0.279	0.040
(t-stat)	(0.503)	(1.398)	(1.517)	(1.068)	(1.532)	(1.720)	(1.055)	(0.201)
Variable	–34.784	–21.674	–12.763	–38.535	–27.418	–22.346	–2.797	–5.046
(t-stat)	(6.135)	(8.900)	(6.549)	(6.376)	(9.086)	(8.293)	(2.658)	(5.113)
Adj. R^2	0.631	0.701	0.577	0.589	0.691	0.647	0.214	0.321
D. Unemployment Rate Change								
Variables in $t-1$								
r	–0.015	–0.014	–0.007	–0.010	–0.018	–0.006	0.007	0.027
(t-stat)	(1.465)	(1.531)	(0.769)	(0.761)	(1.971)	(0.757)	(0.762)	(1.420)
term	0.003	–0.010	–0.020	–0.003	–0.029	–0.052	–0.039	–0.041
(t-stat)	(0.194)	(0.786)	(1.523)	(0.178)	(2.252)	(3.143)	(1.220)	(1.143)
Lag	0.534	0.501	0.413	0.466	0.497	0.508	0.869	0.718
(t-stat)	(4.850)	(4.896)	(3.928)	(3.356)	(4.643)	(5.066)	(8.093)	(8.204)
Variable	0.962	0.583	0.435	1.225	0.748	0.621	0.029	0.101
(t-stat)	(3.673)	(4.382)	(4.738)	(4.389)	(4.277)	(3.641)	(1.824)	(1.850)
Adj. R^2	0.799	0.805	0.837	0.824	0.808	0.808	0.698	0.720

(*continued*)

Table B.1. (Continued)

	3-Month RRI $\left(\boldsymbol{RRI}_{3m,3m}^{(xm)}\right)$			12-Month RRI $\left(\boldsymbol{RRI}_{12m,12m}^{(xm)}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
Variables in $t-2$								
r	–0.055	–0.051	–0.033	–0.043	–0.061	–0.031	0.014	0.055
(t-stat)	(2.326)	(2.198)	(1.426)	(1.457)	(2.776)	(1.612)	(0.356)	(1.661)
term	–0.033	–0.058	–0.093	–0.058	–0.113	–0.174	–0.169	–0.157
(t-stat)	(0.710)	(1.257)	(1.329)	(1.124)	(2.481)	(2.947)	(1.348)	(1.225)
Lag	0.426	0.349	0.355	0.405	0.361	0.393	0.856	0.656
(t-stat)	(3.644)	(2.730)	(2.876)	(3.179)	(2.872)	(3.097)	(4.028)	(3.489)
Variable	2.627	1.612	0.979	2.977	2.021	1.610	0.111	0.278
(t-stat)	(6.548)	(7.145)	(10.465)	(8.947)	(7.246)	(5.687)	(1.822)	(2.716)
Adj. R^2	0.831	0.841	0.805	0.832	0.838	0.810	0.589	0.628
Variables in $t-4$								
r	–0.095	–0.071	–0.033	–0.061	–0.092	–0.017	0.166	0.222
(t-stat)	(1.435)	(1.028)	(0.413)	(0.726)	(1.400)	(0.260)	(1.208)	(2.359)
term	–0.095	–0.115	–0.195	–0.145	–0.232	–0.359	–0.396	–0.337
(t-stat)	(0.548)	(0.680)	(0.729)	(0.698)	(1.390)	(1.705)	(0.900)	(0.781)
Lag	0.268	0.136	0.165	0.244	0.129	0.145	0.629	0.394
(t-stat)	(1.708)	(0.788)	(0.711)	(1.295)	(0.737)	(0.711)	(1.648)	(1.169)
Variable	6.168	3.724	2.109	6.622	4.694	3.726	0.390	0.753
(t-stat)	(10.153)	(13.662)	(8.564)	(7.612)	(11.652)	(9.580)	(2.138)	(4.422)
Adj. R^2	0.785	0.800	0.665	0.730	0.789	0.716	0.317	0.400

Note: This table reports predictive regressions for euro-area real activity variables. Predictive horizons are one, two, and four quarters. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. The sample period runs from January 2005 to December 2019.

Table B.2. Predicting Euro-Area Bank Lending Variables

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
A. Bank Lending Growth								
Variables in $t-1$								
r	0.159	0.158	0.153	0.156	0.164	0.148	0.026	0.041
(t-stat)	(3.406)	(3.527)	(3.314)	(3.520)	(3.605)	(3.209)	(0.346)	(0.681)
term	0.048	0.078	0.086	0.060	0.110	0.137	0.067	0.106
(t-stat)	(1.069)	(1.548)	(1.640)	(1.266)	(2.109)	(2.478)	(1.208)	(2.087)
Lag	0.842	0.844	0.821	0.826	0.843	0.825	0.745	0.748
(t-stat)	(17.177)	(17.170)	(15.928)	(16.189)	(17.286)	(16.410)	(14.465)	(14.309)
Variable	–1.781	–1.012	–0.626	–2.006	–1.287	–1.068	–0.239	–0.389
(t-stat)	(6.058)	(5.812)	(4.826)	(7.394)	(5.833)	(4.629)	(3.594)	(3.271)
Adj. R^2	0.836	0.835	0.834	0.837	0.835	0.835	0.827	0.839
Variables in $t-2$								
r	0.455	0.456	0.437	0.445	0.478	0.424	0.035	0.096
(t-stat)	(3.984)	(4.366)	(3.865)	(4.190)	(4.559)	(4.003)	(0.174)	(0.616)
term	0.244	0.342	0.335	0.280	0.457	0.522	0.223	0.356
(t-stat)	(1.874)	(2.200)	(1.843)	(1.927)	(2.792)	(2.880)	(1.410)	(1.997)
Lag	0.834	0.831	0.773	0.802	0.829	0.785	0.627	0.653
(t-stat)	(12.438)	(12.001)	(10.349)	(11.515)	(12.348)	(11.341)	(9.008)	(9.136)
Variable	–6.348	–3.566	–2.045	–6.929	–4.515	–3.604	–0.755	–1.170
(t-stat)	(5.864)	(6.459)	(4.936)	(7.469)	(6.951)	(5.193)	(3.741)	(3.113)
Adj. R^2	0.845	0.839	0.822	0.843	0.839	0.831	0.802	0.825

(*continued*)

Table B.2. (Continued)

	3-Month RRI $\left(\boldsymbol{RRI}^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(\boldsymbol{RRI}^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
Variables in $t-4$								
r	1.198	1.227	1.220	1.184	1.306	1.169	0.039	0.254
(t-stat)	(4.296)	(5.119)	(4.652)	(4.273)	(5.623)	(5.495)	(0.095)	(0.770)
term	0.703	1.051	0.998	0.811	1.429	1.611	0.553	0.977
(t-stat)	(2.193)	(2.818)	(2.169)	(2.334)	(3.653)	(3.727)	(1.600)	(2.044)
Lag	0.780	0.778	0.662	0.723	0.777	0.688	0.396	0.476
(t-stat)	(7.902)	(8.394)	(6.455)	(7.843)	(9.223)	(8.552)	(3.015)	(4.300)
Variable	–19.168	–11.199	–6.268	–20.592	–14.279	–11.320	–2.244	–3.282
(t-stat)	(5.662)	(7.938)	(6.030)	(8.018)	(9.247)	(7.318)	(4.319)	(3.412)
Adj. R^2	0.833	0.844	0.803	0.828	0.848	0.836	0.761	0.791
B. Consumer Loan Growth								
Variables in $t-1$								
r	0.043	0.049	0.027	0.031	0.052	0.031	–0.137	–0.102
(t-stat)	(0.832)	(0.942)	(0.500)	(0.581)	(1.001)	(0.630)	(2.387)	(2.351)
term	–0.224	–0.194	–0.197	–0.212	–0.168	–0.145	–0.185	–0.170
(t-stat)	(2.326)	(1.896)	(1.788)	(2.069)	(1.575)	(1.287)	(1.784)	(1.666)
Lag	0.588	0.584	0.589	0.595	0.583	0.569	0.503	0.504
(t-stat)	(6.305)	(6.369)	(6.586)	(6.431)	(6.419)	(6.315)	(5.173)	(6.063)
Variable	–1.497	–0.971	–0.433	–1.400	–1.187	–0.978	–0.288	–0.397
(t-stat)	(3.023)	(3.825)	(2.086)	(2.649)	(3.693)	(3.187)	(2.456)	(3.053)
Adj. R^2	0.657	0.664	0.647	0.649	0.662	0.660	0.669	0.669

(continued)

Table B.2. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$				
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GM Spread**
Variables in $t-2$								
r	0.144	0.157	0.109	0.112	0.170	0.107	–0.359	–0.287
(t-stat)	(1.040)	(1.113)	(0.768)	(0.771)	(1.210)	(0.801)	(2.846)	(2.653)
term	–0.539	–0.436	–0.413	–0.490	–0.348	–0.275	–0.475	–0.414
(t-stat)	(2.288)	(1.749)	(1.573)	(1.920)	(1.362)	(1.050)	(1.712)	(1.518)
Lag	0.477	0.480	0.471	0.484	0.479	0.451	0.365	0.341
(t-stat)	(3.333)	(3.426)	(3.327)	(3.335)	(3.410)	(3.146)	(2.941)	(2.535)
Variable	–5.009	–3.055	–1.692	–5.015	–3.759	–3.154	–0.746	–1.143
(t-stat)	(4.387)	(5.610)	(4.158)	(4.666)	(5.847)	(5.095)	(2.953)	(3.539)
Adj. R^2	0.682	0.693	0.670	0.666	0.688	0.685	0.673	0.687
Variables in $t-4$								
r	0.546	0.572	0.458	0.468	0.623	0.443	–0.617	–0.491
(t-stat)	(1.671)	(1.688)	(1.318)	(1.299)	(1.861)	(1.380)	(1.916)	(1.746)
term	–0.877	–0.589	–0.514	–0.718	–0.311	–0.149	–0.867	–0.640
(t-stat)	(1.493)	(1.006)	(0.772)	(1.108)	(0.530)	(0.241)	(1.193)	(0.850)
Lag	0.423	0.431	0.416	0.433	0.433	0.391	0.298	0.257
(t-stat)	(2.264)	(2.378)	(2.220)	(2.211)	(2.398)	(2.093)	(1.637)	(1.544)
Variable	–14.219	–8.388	–4.669	–14.517	–10.541	–8.533	–1.547	–2.634
(t-stat)	(7.496)	(9.119)	(6.394)	(7.516)	(9.884)	(8.187)	(2.884)	(4.667)
Adj. R^2	0.778	0.789	0.738	0.745	0.786	0.767	0.667	0.719

(continued)

Table B.2. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
C. Real Estate Loan Growth								
Variables in $t-1$								
r	0.069	0.069	0.060	0.066	0.072	0.061	–0.015	–0.002
(t-stat)	(1.767)	(1.670)	(1.480)	(1.686)	(1.670)	(1.490)	(0.451)	(0.052)
term	0.027	0.044	0.052	0.038	0.063	0.084	0.057	0.062
(t-stat)	(0.526)	(0.752)	(0.742)	(0.682)	(0.960)	(1.046)	(0.771)	(0.715)
Lag	0.796	0.796	0.795	0.791	0.797	0.788	0.803	0.788
(t-stat)	(9.753)	(10.273)	(9.737)	(8.965)	(10.717)	(10.714)	(11.033)	(10.521)
Variable	–1.071	–0.608	–0.348	–1.215	–0.764	–0.646	–0.114	–0.168
(t-stat)	(2.368)	(2.532)	(2.115)	(2.804)	(2.448)	(2.045)	(1.762)	(1.312)
Adj. R^2	0.778	0.777	0.773	0.778	0.777	0.776	0.769	0.769
Variables in $t-2$								
r	0.236	0.233	0.199	0.218	0.248	0.208	–0.038	0.008
(t-stat)	(2.106)	(1.937)	(1.657)	(1.877)	(1.985)	(1.740)	(0.469)	(0.091)
term	0.158	0.211	0.225	0.189	0.279	0.334	0.237	0.261
(t-stat)	(0.968)	(1.144)	(1.007)	(1.058)	(1.397)	(1.400)	(1.019)	(0.997)
Lag	0.710	0.705	0.706	0.703	0.703	0.689	0.706	0.688
(t-stat)	(6.005)	(6.023)	(5.612)	(5.427)	(6.184)	(6.017)	(5.909)	(6.021)
Variable	–3.644	–2.009	–1.053	–3.847	–2.586	–2.079	–0.366	–0.535
(t-stat)	(4.057)	(3.668)	(2.608)	(4.200)	(3.498)	(2.630)	(2.121)	(1.990)
Adj. R^2	0.732	0.726	0.706	0.724	0.727	0.719	0.696	0.696

(*continued*)

Table B.2. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GM Spread
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**		
Variables in $t-4$								
r	0.562	0.566	0.486	0.508	0.604	0.504	–0.277	–0.062
(t-stat)	(1.961)	(1.846)	(1.596)	(1.636)	(1.951)	(1.710)	(1.203)	(0.248)
term	0.606	0.734	0.758	0.659	0.910	1.047	0.798	0.883
(t-stat)	(1.534)	(1.671)	(1.413)	(1.485)	(1.969)	(1.964)	(1.356)	(1.416)
Lag	0.629	0.611	0.598	0.612	0.607	0.578	0.541	0.548
(t-stat)	(4.843)	(4.668)	(4.106)	(4.223)	(4.727)	(4.415)	(4.217)	(4.190)
Variable	–9.978	–5.476	–2.854	–9.857	–6.946	–5.613	–1.255	–1.638
(t-stat)	(5.519)	(5.070)	(3.622)	(4.493)	(4.564)	(3.816)	(2.856)	(3.400)
Adj. R^2	0.713	0.697	0.648	0.677	0.696	0.679	0.651	0.641
D. C&I Loan Growth								
Variables in $t-1$								
r	0.105	0.108	0.111	0.106	0.117	0.102	–0.041	–0.048
(t-stat)	(1.960)	(2.129)	(2.421)	(2.116)	(2.310)	(1.932)	(0.409)	(0.627)
term	0.019	0.033	0.067	0.035	0.073	0.108	–0.009	0.086
(t-stat)	(0.209)	(0.335)	(0.831)	(0.396)	(0.715)	(1.122)	(0.087)	(1.404)
Lag	0.923	0.901	0.884	0.903	0.899	0.875	0.778	0.806
(t-stat)	(17.473)	(18.770)	(23.450)	(18.517)	(19.061)	(21.638)	(12.246)	(15.966)
Variable	–2.438	–1.282	–0.925	–2.815	–1.629	–1.407	–0.302	–0.562
(t-stat)	(5.170)	(4.276)	(6.391)	(6.520)	(4.385)	(5.256)	(4.437)	(4.833)
Adj. R^2	0.882	0.878	0.888	0.887	0.878	0.881	0.876	0.898

Table B.2. (Continued)

	3-Month RRI $\left(\boldsymbol{RRI}_{3m,3m}^{(xm)}\right)$			**12-Month RRI** $\left(\boldsymbol{RRI}_{12m,12m}^{(xm)}\right)$				
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GM Spread**
Variables in $t-2$								
r	0.260	0.282	0.287	0.266	0.318	0.267	–0.147	–0.195
(t-stat)	(1.695)	(2.091)	(2.534)	(1.908)	(2.371)	(1.922)	(0.520)	(0.877)
term	0.146	0.244	0.307	0.189	0.404	0.483	–0.115	0.256
(t-stat)	(0.633)	(0.964)	(1.465)	(0.820)	(1.615)	(2.029)	(0.364)	(1.726)
Lag	0.956	0.926	0.875	0.911	0.921	0.859	0.643	0.724
(t-stat)	(12.902)	(14.723)	(15.770)	(12.762)	(15.736)	(15.246)	(5.467)	(9.429)
Variable	–9.010	–5.019	–3.271	–10.042	–6.374	–5.187	–0.909	–1.712
(t-stat)	(6.533)	(7.506)	(9.637)	(9.162)	(8.339)	(8.836)	(4.155)	(4.306)
Adj. R^2	0.889	0.886	0.903	0.898	0.888	0.890	0.846	0.901
Variables in $t-4$								
r	0.683	0.723	0.762	0.706	0.849	0.707	–0.351	–0.528
(t-stat)	(1.452)	(1.929)	(2.794)	(1.697)	(2.345)	(2.102)	(0.537)	(1.026)
term	0.244	0.824	0.982	0.434	1.376	1.677	–0.480	0.640
(t-stat)	(0.350)	(1.311)	(1.626)	(0.648)	(2.076)	(2.578)	(0.620)	(1.234)
Lag	0.883	0.896	0.802	0.823	0.890	0.787	0.354	0.539
(t-stat)	(7.294)	(9.844)	(8.895)	(7.972)	(9.720)	(8.853)	(1.791)	(4.610)
Variable	–27.828	–16.771	–10.284	–30.724	–21.346	–17.192	–2.757	–4.833
(t-stat)	(5.920)	(10.505)	(10.413)	(10.118)	(11.908)	(12.015)	(4.369)	(4.466)
Adj. R^2	0.830	0.860	0.875	0.850	0.866	0.876	0.755	0.840

Note: This table reports predictive regressions for euro-area bank lending variables. Predictive horizons are one, two, and four quarters. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. The sample period runs from January 2005 to December 2019.

Table B.3. Predicting U.S. Real Activity Variables

Tenor x	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$ 1m	3-Month RRI 3m	3-Month RRI 6m	12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$ 1m	12-Month RRI 3m	12-Month RRI 6m	CDS Spread	GZ Spread	Goldberg Var.
A. Real GDP Growth									
Variables in $t-1$									
r	–0.004	–0.103	–0.125	–0.014	–0.115	–0.168	–0.076	–0.005	–0.062
(t-stat)	(0.075)	(1.933)	(2.225)	(0.273)	(2.075)	(2.326)	(1.534)	(0.107)	(1.560)
term	0.022	–0.050	–0.042	0.010	–0.055	–0.062	0.053	0.093	–0.075
(t-stat)	(0.396)	(0.856)	(0.626)	(0.156)	(0.835)	(0.831)	(0.740)	(1.430)	(1.724)
Lag	–0.148	–0.120	–0.147	–0.121	–0.079	–0.039	0.181	0.046	0.302
(t-stat)	(1.200)	(0.952)	(1.431)	(0.883)	(0.646)	(0.341)	(1.166)	(0.294)	(2.296)
Variable	–2.665	–1.964	–1.258	–3.000	–2.186	–1.610	–0.473	–0.207	–0.033
(t-stat)	(4.377)	(3.568)	(4.627)	(3.564)	(3.390)	(3.285)	(2.196)	(2.361)	(4.747)
Variable									0.035
(t-stat)									(2.258)
Adj. R^2	0.428	0.398	0.343	0.402	0.358	0.308	0.210	0.206	0.179
Variables in $t-2$									
r	–0.054	–0.245	–0.294	–0.066	–0.274	–0.390	–0.196	–0.050	–0.141
(t-stat)	(0.628)	(2.159)	(2.629)	(0.722)	(2.218)	(2.301)	(1.878)	(0.550)	(1.472)
term	0.011	–0.128	–0.119	–0.004	–0.137	–0.162	0.100	0.168	–0.124
(t-stat)	(0.122)	(1.170)	(0.995)	(0.037)	(1.076)	(1.068)	(0.919)	(1.451)	(1.230)
Lag	–0.205	–0.289	–0.334	–0.237	–0.241	–0.207	–0.107	–0.117	0.306
(t-stat)	(1.660)	(1.330)	(1.971)	(1.361)	(1.130)	(1.072)	(1.000)	(0.723)	(3.645)
Variable	–4.907	–4.023	–2.597	–5.942	–4.531	–3.355	–0.969	–0.427	–0.071
(t-stat)	(4.770)	(3.451)	(4.388)	(3.785)	(3.117)	(2.914)	(2.257)	(2.167)	(3.562)
Variable									0.024
(t-stat)									(0.912)
Adj. R^2	0.519	0.502	0.412	0.523	0.461	0.377	0.276	0.208	0.214

(*continued*)

Table B.3. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread	Goldberg Var.
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**			
Variables in $t-4$									
r	–0.343	–0.622	–0.737	–0.357	–0.677	–0.905	–0.602	–0.265	–0.431
(t-stat)	(1.457)	(2.262)	(2.819)	(1.558)	(2.375)	(2.497)	(2.234)	(1.146)	(1.738)
term	–0.121	–0.352	–0.395	–0.154	–0.366	–0.454	0.161	0.252	–0.218
(t-stat)	(0.643)	(1.500)	(1.733)	(0.766)	(1.432)	(1.472)	(0.859)	(1.917)	(1.054)
Lag	–0.241	–0.356	–0.515	–0.327	–0.375	–0.426	–0.240	–0.630	0.162
(t-stat)	(2.800)	(2.400)	(3.436)	(2.920)	(2.309)	(2.196)	(1.387)	(3.142)	(1.208)
Variable	–6.706	–5.760	–4.269	–8.819	–7.083	–5.694	–2.329	–1.099	–0.113
(t-stat)	(4.329)	(4.209)	(4.043)	(4.587)	(3.976)	(3.605)	(2.580)	(4.239)	(3.442)
Variable									0.013
(t-stat)									(0.309)
Adj. R^2	0.426	0.443	0.440	0.481	0.453	0.387	0.428	0.319	0.162
B. Real Consumption Growth									
Variables in $t-1$									
r	–0.032	–0.095	–0.104	–0.038	–0.107	–0.143	–0.088	–0.025	–0.055
(t-stat)	(0.839)	(2.149)	(3.254)	(1.008)	(2.403)	(3.051)	(2.930)	(0.628)	(1.633)
term	–0.019	–0.065	–0.054	–0.027	–0.069	–0.071	0.033	0.039	–0.046
(t-stat)	(0.500)	(1.582)	(1.608)	(0.694)	(1.614)	(1.645)	(0.643)	(0.875)	(1.421)
Lag	0.079	0.040	0.074	–0.012	0.038	0.079	0.138	0.237	0.476
(t-stat)	(0.687)	(0.291)	(0.545)	(0.094)	(0.276)	(0.594)	(1.154)	(1.631)	(3.394)
Variable	–1.533	–1.272	–0.767	–2.108	–1.533	–1.152	–0.475	–0.129	–0.009
(t-stat)	(4.237)	(4.502)	(4.309)	(4.965)	(4.534)	(4.672)	(3.119)	(3.257)	(1.102)
Variable									0.023
(t-stat)									(1.534)
Adj. R^2	0.410	0.429	0.393	0.457	0.429	0.404	0.384	0.311	0.250

(*continued*)

Table B.3. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$					
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GZ Spread**	**Goldberg Var.**
Variables in $t-2$									
r	–0.101	–0.182	–0.205	–0.110	–0.206	–0.252	–0.186	–0.099	–0.118
(t-stat)	(1.267)	(2.031)	(2.793)	(1.386)	(2.267)	(2.780)	(2.698)	(1.222)	(1.544)
term	–0.016	–0.076	–0.074	–0.035	–0.091	–0.092	0.068	0.029	–0.024
(t-stat)	(0.202)	(0.898)	(0.940)	(0.439)	(1.048)	(1.087)	(0.768)	(0.279)	(0.286)
Lag	0.347	0.305	0.280	0.228	0.268	0.318	0.324	0.607	0.665
(t-stat)	(3.524)	(2.621)	(2.142)	(2.214)	(2.363)	(2.807)	(3.177)	(3.064)	(5.466)
Variable	–2.010	–1.665	–1.102	–2.995	–2.153	–1.531	–0.750	–0.068	–0.021
(t-stat)	(3.791)	(4.010)	(3.062)	(4.573)	(4.071)	(3.941)	(3.576)	(0.605)	(1.901)
Variable									0.026
(t-stat)									(1.730)
Adj. R^2	0.557	0.557	0.542	0.591	0.566	0.540	0.575	0.473	0.487
Variables in $t-4$									
r	–0.332	–0.519	–0.603	–0.355	–0.579	–0.733	–0.594	–0.311	–0.329
(t-stat)	(1.588)	(2.259)	(2.774)	(1.759)	(2.547)	(2.966)	(3.089)	(1.437)	(1.640)
term	0.006	–0.163	–0.205	–0.060	–0.209	–0.261	0.144	0.180	0.057
(t-stat)	(0.029)	(0.786)	(1.071)	(0.334)	(1.061)	(1.363)	(0.912)	(0.831)	(0.246)
Lag	0.207	0.105	–0.006	0.070	0.035	0.015	–0.062	0.297	0.564
(t-stat)	(1.597)	(0.693)	(0.046)	(0.581)	(0.240)	(0.093)	(0.510)	(1.417)	(3.710)
Variable	–4.109	–3.661	–2.732	–6.077	–4.928	–3.917	–2.138	–0.337	–0.072
(t-stat)	(3.715)	(4.325)	(3.414)	(4.281)	(4.300)	(4.340)	(4.265)	(1.913)	(2.790)
Variable									0.002
(t-stat)									(0.058)
Adj. R^2	0.503	0.517	0.523	0.557	0.547	0.511	0.613	0.394	0.402

(*continued*)

Table B.3. (Continued)

Tenor x	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$ 1m	3m	6m	12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$ 1m	3m	6m	CDS Spread	GZ Spread	Goldberg Var.
C. Real Investment Growth									
Variables in $t-1$									
r	–0.033	–0.326	–0.423	–0.066	–0.352	–0.500	–0.150	–0.021	–0.106
(t-stat)	(0.346)	(2.247)	(2.364)	(0.627)	(2.246)	(2.262)	(1.679)	(0.280)	(1.374)
term	0.346	0.127	0.149	0.301	0.110	0.082	0.277	0.643	0.013
(t-stat)	(3.061)	(0.989)	(1.204)	(2.310)	(0.761)	(0.511)	(1.900)	(3.233)	(0.107)
Lag	0.317	0.294	0.223	0.327	0.332	0.350	0.618	0.279	0.643
(t-stat)	(2.495)	(1.834)	(1.368)	(2.103)	(2.121)	(2.514)	(4.918)	(1.437)	(7.225)
Variable	–7.459	–5.575	–3.832	–8.274	–6.099	–4.532	–0.774	–0.794	–0.141
(t-stat)	(4.360)	(3.009)	(3.189)	(3.025)	(2.646)	(2.474)	(1.645)	(2.440)	(3.674)
Variable									0.023
(t-stat)									(0.840)
Adj. R^2	0.715	0.670	0.639	0.680	0.639	0.604	0.510	0.566	0.585
Variables in $t-2$									
r	–0.187	–0.833	–1.069	–0.253	–0.896	–1.267	–0.476	–0.207	–0.280
(t-stat)	(0.727)	(1.852)	(2.118)	(0.888)	(1.781)	(1.740)	(1.505)	(0.959)	(1.194)
term	0.788	0.322	0.315	0.713	0.286	0.182	0.864	1.503	0.235
(t-stat)	(2.448)	(0.760)	(0.786)	(1.985)	(0.607)	(0.338)	(2.458)	(2.937)	(0.654)
Lag	0.191	0.121	0.032	0.180	0.157	0.152	0.439	0.000	0.526
(t-stat)	(1.231)	(0.525)	(0.139)	(0.909)	(0.675)	(0.630)	(2.778)	(0.000)	(5.339)
Variable	–15.654	–12.178	–8.245	–17.831	–13.406	–10.142	–2.343	–1.929	–0.300
(t-stat)	(4.275)	(2.783)	(3.032)	(2.997)	(2.400)	(2.072)	(1.591)	(1.770)	(3.298)
Variable									0.066
(t-stat)									(1.018)
Adj. R^2	0.691	0.634	0.578	0.649	0.585	0.526	0.413	0.470	0.476

(continued)

Table B.3. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			**12-Month RRI** $\left(RRI^{(xm)}_{12m,12m}\right)$					
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GZ Spread**	**Goldberg Var.**
Variables in $t-4$									
r	–0.823	–1.823	–2.195	–0.948	–1.938	–2.487	–1.353	–1.027	–0.823
(t-stat)	(1.018)	(1.677)	(1.964)	(1.106)	(1.639)	(1.624)	(1.464)	(1.159)	(1.236)
term	1.778	1.006	0.926	1.645	0.988	0.778	2.392	2.597	1.163
(t-stat)	(1.902)	(0.869)	(0.813)	(1.596)	(0.793)	(0.553)	(2.900)	(3.146)	(1.428)
Lag	0.163	0.104	0.031	0.132	0.112	0.105	0.290	–0.053	0.431
(t-stat)	(1.443)	(0.667)	(0.202)	(0.914)	(0.658)	(0.548)	(1.603)	(0.245)	(3.377)
Variable	–23.489	–18.088	–12.078	–27.543	–20.566	–14.891	–5.238	–2.967	–0.563
(t-stat)	(4.939)	(3.551)	(3.757)	(3.650)	(2.917)	(2.332)	(1.700)	(3.135)	(5.220)
Variable									0.081
(t-stat)									(0.516)
Adj. R^2	0.597	0.558	0.522	0.577	0.526	0.457	0.433	0.435	0.456
D. Unemployment Rate Change									
Variables in $t-1$									
r	0.018	0.067	0.090	0.024	0.072	0.104	0.032	0.016	0.024
(t-stat)	(1.210)	(3.712)	(4.676)	(1.407)	(3.406)	(3.354)	(2.426)	(0.871)	(1.725)
term	–0.014	0.023	0.023	–0.008	0.024	0.031	–0.014	–0.091	0.014
(t-stat)	(0.925)	(1.208)	(1.382)	(0.412)	(1.071)	(1.181)	(0.612)	(2.049)	(0.630)
Lag	0.409	0.327	0.218	0.380	0.357	0.336	0.675	0.093	0.735
(t-stat)	(6.508)	(3.826)	(2.601)	(4.823)	(3.732)	(3.363)	(5.394)	(0.359)	(6.882)
Variable	1.104	0.908	0.696	1.314	1.020	0.829	0.109	0.192	1.120
(t-stat)	(7.594)	(4.172)	(5.962)	(4.486)	(3.311)	(3.109)	(1.947)	(2.637)	(0.982)
Variable									–0.288
(t-stat)									(0.460)
Adj. R^2	0.760	0.735	0.756	0.745	0.715	0.698	0.592	0.701	0.593

(*continued*)

Table B.3. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			**12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$**					
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GZ Spread**	**Goldberg Var.**
Variables in $t-2$									
r	0.050	0.164	0.210	0.064	0.178	0.253	0.093	0.062	0.046
(t-stat)	(1.456)	(3.041)	(3.947)	(1.644)	(2.823)	(2.551)	(2.119)	(1.421)	(1.428)
term	–0.055	0.032	0.040	–0.038	0.038	0.061	–0.086	–0.193	–0.012
(t-stat)	(1.892)	(0.671)	(0.935)	(0.978)	(0.640)	(0.805)	(1.554)	(3.010)	(0.298)
Lag	0.323	0.217	0.116	0.277	0.237	0.208	0.560	–0.075	0.715
(t-stat)	(6.319)	(1.810)	(0.997)	(3.066)	(1.681)	(1.156)	(3.525)	(0.246)	(5.431)
Variable	2.531	2.083	1.474	3.033	2.369	1.879	0.382	0.417	4.244
(t-stat)	(7.307)	(4.187)	(5.548)	(4.539)	(3.300)	(2.727)	(1.683)	(2.790)	(2.360)
Variable									–0.624
(t-stat)									(0.616)
Adj. R^2	0.821	0.787	0.764	0.800	0.751	0.703	0.574	0.670	0.612
Variables in $t-4$									
r	0.197	0.424	0.516	0.235	0.464	0.628	0.320	0.259	0.168
(t-stat)	(1.599)	(2.575)	(3.386)	(1.778)	(2.532)	(2.535)	(1.975)	(1.764)	(1.581)
term	–0.142	0.047	0.079	–0.094	0.063	0.137	–0.267	–0.285	–0.106
(t-stat)	(1.318)	(0.291)	(0.534)	(0.691)	(0.339)	(0.591)	(2.133)	(2.779)	(1.184)
Lag	0.185	0.078	–0.021	0.113	0.062	0.007	0.290	–0.141	0.547
(t-stat)	(3.071)	(0.716)	(0.223)	(1.209)	(0.486)	(0.048)	(1.602)	(0.800)	(3.555)
Variable	4.825	3.922	2.713	5.907	4.646	3.693	1.105	0.681	9.667
(t-stat)	(6.801)	(5.188)	(6.051)	(5.313)	(4.244)	(3.661)	(1.816)	(4.356)	(3.472)
Variable									–2.339
(t-stat)									(0.818)
Adj. R^2	0.702	0.683	0.664	0.697	0.655	0.591	0.471	0.545	0.448

Note: This table reports predictive regressions for U.S. real activity variables. Predictive horizons are one, two, and four quarters. “Goldberg (2020) var.” denotes the liquidity supply and demand variables, respectively. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. The sample period runs from January 2005 to December 2019.

Table B.4. Predicting U.S. Bank Lending Variables

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$					
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GZ Spread**	**Goldberg Var.**
				A. Bank Lending Growth					
Variables in $t-1$									
r	0.042	0.006	–0.015	0.046	–0.006	–0.061	0.010	0.072	0.004
(t-stat)	(0.446)	(0.068)	(0.147)	(0.489)	(0.067)	(0.580)	(0.102)	(0.653)	(0.039)
term	–0.296	–0.317	–0.282	–0.292	–0.317	–0.319	–0.309	–0.195	–0.348
(t-stat)	(1.710)	(2.113)	(2.029)	(1.851)	(2.320)	(2.528)	(1.616)	(1.121)	(2.053)
Lag	0.186	0.177	0.197	0.176	0.170	0.162	0.147	0.167	0.217
(t-stat)	(1.248)	(1.329)	(1.684)	(1.353)	(1.444)	(1.532)	(1.066)	(1.304)	(1.359)
Variable	–0.867	–0.885	–0.916	–1.316	–1.334	–1.348	–0.195	–0.176	–0.027
(t-stat)	(0.958)	(1.245)	(2.524)	(1.280)	(1.768)	(2.329)	(0.623)	(1.871)	(1.279)
Variable									0.039
(t-stat)									(1.250)
Adj. R^2	0.260	0.273	0.315	0.272	0.290	0.315	0.252	0.286	0.252
Variables in $t-2$									
r	0.110	0.007	–0.043	0.117	–0.028	–0.180	–0.003	0.209	0.020
(t-stat)	(0.576)	(0.035)	(0.227)	(0.626)	(0.151)	(0.926)	(0.015)	(0.883)	(0.094)
term	–0.524	–0.555	–0.453	–0.521	–0.578	–0.592	–0.403	–0.149	–0.736
(t-stat)	(1.398)	(1.753)	(1.442)	(1.536)	(1.997)	(2.257)	(1.017)	(0.353)	(1.711)
Lag	0.141	0.147	0.191	0.123	0.125	0.118	0.104	0.171	0.059
(t-stat)	(0.813)	(0.977)	(1.386)	(0.808)	(0.932)	(0.973)	(0.646)	(1.017)	(0.260)
Variable	–2.623	–2.832	–2.474	–3.735	–3.775	–3.704	–1.129	–0.532	0.025
(t-stat)	(1.781)	(2.323)	(3.646)	(2.117)	(2.867)	(3.734)	(1.866)	(3.262)	(0.641)
Variable									0.007
(t-stat)									(0.093)
Adj. R^2	0.353	0.405	0.483	0.380	0.431	0.493	0.385	0.434	0.290

(*continued*)

Table B.4. (Continued)

Tenor x	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$ 1m	3m	6m	12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$ 1m	3m	6m	CDS Spread	GZ Spread	Goldberg Var.
Variables in $t-4$									
r	0.330	–0.016	–0.133	0.333	–0.086	–0.446	–0.008	0.504	0.059
(t-stat)	(1.013)	(0.052)	(0.496)	(1.043)	(0.294)	(1.838)	(0.021)	(1.329)	(0.160)
term	–0.530	–0.731	–0.468	–0.590	–0.812	–0.845	–0.416	0.380	–1.157
(t-stat)	(1.033)	(1.648)	(1.145)	(1.228)	(1.901)	(2.440)	(0.589)	(0.609)	(1.606)
Lag	0.243	0.239	0.320	0.197	0.191	0.198	0.156	0.323	0.183
(t-stat)	(1.977)	(2.136)	(3.620)	(1.687)	(1.773)	(2.228)	(0.947)	(2.272)	(0.944)
Variable	–9.237	–8.063	–6.054	–11.675	–10.089	–9.055	–2.789	–1.343	–0.071
(t-stat)	(6.022)	(6.749)	(9.907)	(6.028)	(7.279)	(11.004)	(2.627)	(5.803)	(0.964)
Variable									0.039
(t-stat)									(0.446)
Adj. R^2	0.614	0.682	0.766	0.658	0.714	0.792	0.561	0.671	0.366
				B. Consumer Loan Growth					
Variables in $t-1$									
r	–0.277	–0.194	–0.182	–0.224	–0.185	–0.196	–0.187	–0.115	–0.221
(t-stat)	(1.769)	(1.309)	(1.129)	(1.553)	(1.196)	(1.149)	(1.151)	(0.661)	(1.181)
term	–0.662	–0.522	–0.469	–0.567	–0.488	–0.455	–0.473	–0.323	–0.556
(t-stat)	(2.686)	(2.643)	(2.137)	(2.656)	(2.469)	(2.234)	(2.495)	(1.350)	(2.111)
Lag	0.285	0.370	0.411	0.346	0.397	0.424	0.395	0.450	0.289
(t-stat)	(2.190)	(3.384)	(3.080)	(3.051)	(3.516)	(3.480)	(3.426)	(3.293)	(1.558)
Variable	1.303	0.222	–0.148	0.738	–0.103	–0.455	–0.073	–0.135	0.048
(t-stat)	(1.096)	(0.247)	(0.303)	(0.535)	(0.107)	(0.657)	(0.214)	(1.190)	(1.122)
Variable									–0.052
(t-stat)									(1.512)
Adj. R^2	0.380	0.366	0.366	0.369	0.365	0.369	0.366	0.378	0.385

(*continued*)

Table B.4. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$			CDS Spread	GZ Spread	Goldberg Var.
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**			
Variables in $t-2$									
r	–0.349	–0.287	–0.211	–0.294	–0.304	–0.399	–0.387	0.120	–0.524
(t-stat)	(1.003)	(1.027)	(0.688)	(1.003)	(1.035)	(1.243)	(1.129)	(0.432)	(1.248)
term	–1.079	–0.862	–0.530	–0.978	–0.840	–0.744	–0.971	–0.007	–1.354
(t-stat)	(1.579)	(1.813)	(1.335)	(1.769)	(1.982)	(1.936)	(1.897)	(0.021)	(2.002)
Lag	0.334	0.434	0.567	0.369	0.444	0.492	0.335	0.576	0.185
(t-stat)	(1.419)	(2.538)	(4.080)	(1.912)	(3.039)	(3.882)	(1.941)	(4.809)	(0.800)
Variable	–0.740	–2.055	–2.534	–1.791	–2.898	–3.342	–0.556	–0.734	0.085
(t-stat)	(0.284)	(1.125)	(3.592)	(0.629)	(1.590)	(2.799)	(0.839)	(4.138)	(1.270)
Variable									–0.051
(t-stat)									(0.929)
Adj. R^2	0.404	0.419	0.458	0.408	0.429	0.459	0.412	0.489	0.411
Variables in $t-4$									
r	–0.781	–0.824	–0.747	–0.708	–0.888	–1.115	–1.058	0.173	–1.266
(t-stat)	(0.816)	(0.960)	(0.894)	(0.793)	(1.053)	(1.408)	(1.248)	(0.219)	(1.552)
term	–2.629	–2.385	–1.925	–2.484	–2.395	–2.168	–2.535	–0.343	–3.323
(t-stat)	(1.613)	(1.690)	(1.501)	(1.705)	(1.827)	(1.886)	(2.217)	(0.321)	(2.581)
Lag	0.210	0.299	0.403	0.237	0.294	0.366	0.161	0.489	0.047
(t-stat)	(0.802)	(1.257)	(1.806)	(0.992)	(1.318)	(1.770)	(0.821)	(2.222)	(0.210)
Variable	–4.821	–6.112	–5.323	–7.255	–7.683	–8.293	–1.847	–1.802	0.164
(t-stat)	(1.446)	(2.441)	(3.128)	(1.994)	(2.625)	(3.586)	(1.559)	(4.062)	(1.774)
Variable									0.083
(t-stat)									(0.618)
Adj. R^2	0.513	0.546	0.574	0.528	0.555	0.602	0.526	0.650	0.513

(continued)

Table B.4. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$					
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GZ Spread**	**Goldberg Var.**
C. Real Estate Loan Growth									
Variables in $t-1$									
r	0.029	0.010	–0.017	0.020	0.013	0.007			
(t-stat)	(0.138)	(0.148)	(0.040)	(0.215)	(0.074)	(0.123)	(0.148)	(0.095)	(0.051)
term	–0.489	–0.480	–0.443	–0.462	–0.463	–0.458	–0.476	–0.511	–0.475
(t-stat)	(1.704)	(1.944)	(1.923)	(1.779)	(2.106)	(2.207)	(1.764)	(1.579)	(2.247)
Lag	0.288	0.293	0.319	0.300	0.303	0.307	0.290	0.282	0.326
(t-stat)	(1.164)	(1.271)	(1.477)	(1.367)	(1.492)	(1.567)	(1.494)	(1.190)	(1.574)
Variable	0.053	–0.076	–0.387	–0.411	–0.582	–0.641	–0.033	0.025	–0.015
(t-stat)	(0.039)	(0.071)	(0.635)	(0.256)	(0.475)	(0.673)	(0.082)	(0.181)	(0.584)
Variable									0.032
(t-stat)									(1.264)
Adj. R^2	0.419	0.419	0.426	0.421	0.424	0.428	0.419	0.419	0.414
Variables in $t-2$									
r	–0.007	–0.028	–0.070	0.016	–0.050	–0.146	–0.038	0.060	–0.014
(t-stat)	(0.026)	(0.120)	(0.302)	(0.066)	(0.213)	(0.595)	(0.162)	(0.237)	(0.058)
term	–0.747	–0.702	–0.602	–0.692	–0.687	–0.668	–0.553	–0.442	–0.792
(t-stat)	(1.553)	(1.713)	(1.620)	(1.587)	(1.891)	(2.042)	(1.341)	(0.895)	(1.919)
Lag	0.409	0.426	0.464	0.417	0.426	0.438	0.404	0.470	0.368
(t-stat)	(1.860)	(2.087)	(2.415)	(2.106)	(2.334)	(2.505)	(2.249)	(2.194)	(1.647)
Variable	–0.282	–1.066	–1.397	–1.410	–1.998	–2.208	–0.822	–0.265	0.060
(t-stat)	(0.147)	(0.662)	()1.511)	(0.585)	(1.090)	(1.567)	(1.604)	(1.235)	(1.812)
Variable									–0.016
(t-stat)									(0.211)
Adj. R^2	0.529	0.536	0.558	0.534	0.547	0.563	0.552	0.544	0.531

(*continued*)

Table B.4. (Continued)

	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$					
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GZ Spread**	**Goldberg Var.**
Variables in $t-4$									
r	–0.327	–0.520	–0.667	–0.289	–0.565	–0.891	–0.477	–0.200	–0.452
(t-stat)	(0.725)	(1.217)	(1.670)	(0.666)	(1.360)	(2.285)	(1.076)	(0.470)	(0.975)
term	–1.216	–1.240	–0.970	–1.161	–1.248	–1.179	–0.966	0.015	–1.514
(t-stat)	(1.167)	(1.337)	(1.139)	(1.226)	(1.457)	(1.578)	(1.070)	(0.019)	(1.509)
Lag	0.512	0.528	0.589	0.506	0.514	0.546	0.464	0.669	0.475
(t-stat)	(2.721)	(3.248)	(4.475)	(3.041)	(3.550)	(4.623)	(2.687)	(4.496)	(2.202)
Variable	–4.558	–4.978	–4.539	–7.143	–7.010	–7.144	–2.226	–1.186	0.065
(t-stat)	(1.973)	(2.605)	(3.552)	(2.411)	(3.124)	(4.246)	(2.414)	(4.567)	(0.834)
Variable									0.035
(t-stat)									(0.406)
Adj. R^2	0.674	0.701	0.747	0.696	0.722	0.764	0.702	0.742	0.644
D. C&I Loan Growth									
Variables in $t-1$									
r	0.331	0.172	0.118	0.308	0.139	0.009	0.181	0.395	0.215
(t-stat)	(3.107)	(1.604)	(0.952)	(2.607)	(1.166)	(0.067)	(1.312)	(3.391)	(1.997)
term	0.297	0.148	0.190	0.241	0.118	0.069	0.238	0.530	0.096
(t-stat)	(1.842)	(0.932)	(1.540)	(1.475)	(0.712)	(0.402)	(1.001)	(4.438)	(0.523)
Lag	0.861	0.824	0.814	0.831	0.806	0.774	0.816	0.744	0.929
(t-stat)	(11.03)	(12.24)	(15.06)	(11.72)	(12.28)	(12.37)	(11.51)	(15.54)	(10.05)
Variable	–3.955	–3.107	–2.570	–4.486	–3.749	–3.260	–0.769	–0.653	–0.125
(t-stat)	(3.476)	(3.569)	(5.672)	(3.088)	(3.306)	(3.629)	(1.492)	(5.957)	(2.266)
Variable									0.074
(t-stat)									(0.955)
Adj. R^2	0.768	0.772	0.814	0.765	0.773	0.782	0.722	0.814	0.749

(*continued*)

Table B.4. (Continued)

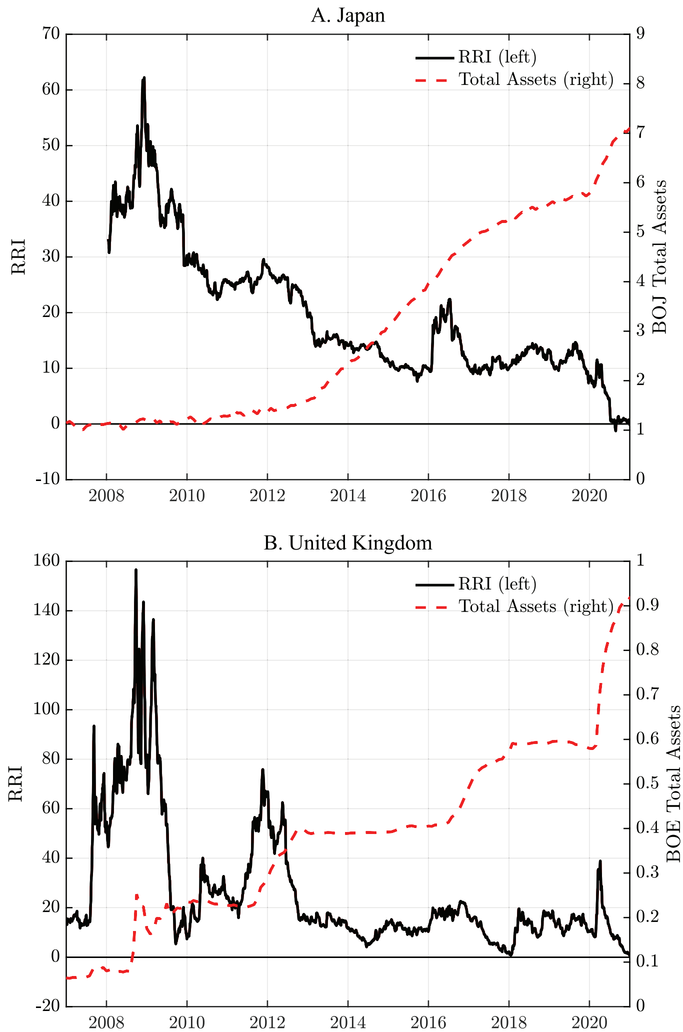
	3-Month RRI $\left(RRI^{(xm)}_{3m,3m}\right)$			12-Month RRI $\left(RRI^{(xm)}_{12m,12m}\right)$					
Tenor x	**1m**	**3m**	**6m**	**1m**	**3m**	**6m**	**CDS Spread**	**GZ Spread**	**Goldberg Var.**
Variables in $t-2$									
r	1.059	0.567	0.409	0.991	0.440	–0.013	0.552	1.282	0.624
(t-stat)	(3.147)	(1.779)	(1.240)	(2.697)	(1.253)	(0.036)	(1.195)	(4.343)	(1.429)
term	0.996	0.622	0.737	0.847	0.468	0.257	1.118	1.900	0.136
(t-stat)	(1.877)	(1.309)	(2.072)	(1.610)	(0.946)	(0.560)	(1.705)	(5.591)	(0.152)
Lag	0.782	0.746	0.740	0.740	0.707	0.652	0.734	0.654	0.732
(t-stat)	(6.491)	(6.798)	(8.562)	(6.617)	(6.844)	(7.260)	(8.701)	(11.049)	(5.659)
Variable	–12.384	–10.483	–7.926	–14.488	–12.263	–10.590	–3.432	–2.101	–0.143
(t-stat)	(5.344)	(4.645)	(6.827)	(4.165)	(4.014)	(4.488)	(1.863)	(8.747)	(1.457)
Variable									0.150
(t-stat)									(0.705)
Adj. R^2	0.694	0.735	0.809	0.697	0.727	0.757	0.633	0.847	0.533
Variables in $t-4$									
r	2.145	0.798	0.502	1.968	0.431	–0.812	0.690	2.830	0.560
(t-stat)	(2.337)	(0.956)	(0.643)	(2.006)	(0.465)	(0.920)	(0.473)	(4.138)	(0.366)
term	0.800	–0.141	0.374	0.471	–0.572	–1.120	0.741	3.690	–2.326
(t-stat)	(0.502)	(0.111)	(0.402)	(0.322)	(0.431)	(1.021)	(0.336)	(4.111)	(0.741)
Lag	0.387	0.357	0.386	0.335	0.293	0.234	0.290	0.337	0.191
(t-stat)	(3.853)	(3.383)	(4.133)	(3.616)	(3.007)	(2.573)	(2.319)	(4.093)	(0.972)
Variable	–34.528	–28.842	–20.605	–40.960	–33.598	–28.601	–8.539	–5.379	–0.215
(t-stat)	(10.63)	(7.673)	(10.07)	(7.078)	(6.256)	(7.221)	(1.809)	(15.43)	(0.931)
Variable									0.438
(t-stat)									(0.984)
Adj. R^2	0.589	0.668	0.750	0.613	0.657	0.718	0.408	0.812	0.230

Note: This table reports predictive regressions for U.S. bank lending variables. Predictive horizons are one, two, and four quarters. "Goldberg (2020) var." denotes the liquidity supply and demand variables, respectively. Presented are the parameter estimates, Newey-West adjusted t-statistics in parentheses, and adjusted R^2 values. The sample period runs from January 2005 to December 2019.

Appendix C. Data for Japan and the United Kingdom

This appendix displays the RRI and the total assets of the central bank for Japan and the United Kingdom.

Figure C.1. Rollover Risk Indicator and Central Banks Total Assets in Japan and the United Kingdom



Note: Panel A displays the three-month rollover risk indicator (in bp) and the Bank of Japan total assets (in JPY trillion). Panel B displays the three-month rollover risk indicator (in bp) and the Bank of England total assets (in GBP trillion). The spread series are smoothed using a five-day moving average. The sample periods are January 2007 to December 2020.

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