Volume 15, Number 2

June 2019

IJCB INTERNATIONAL JOURNAL OF CENTRAL BANKING Volume 15, Number 2 June 2019

INTERNATIONAL JOURNAL OF CENTRAL BANKING

International Journal of Central Banking

Volume 15, Number 2 June 2019

*The contents of this journal, together with additional materials provided by article authors, are available without charge at **www.ijcb.org**.*

The *International Journal of Central Banking* is published quarterly (ISSN: 1815-4654). Online access to the publication is available free of charge at **www.ijcb.org**. Individual print subscriptions are available. Orders may be placed by phone (001 216 579 3125), via fax (001 216 579 2886), or by e-mail (editor@ijcb.org).

Renewals, claims, address changes, and requests for permission to reprint material from this journal should be addressed to:

International Journal of Central Banking
Executive Office Department
Federal Reserve Bank of Cleveland
P.O. Box 6387
Cleveland, OH 44101-1387
USA

Phone: 001 216 579 3125
Fax: 001 216 579 2886
E-mail: editor@ijcb.org

ISSN: 1815-4654

The Tradeoff between Monetary Policy and Bank Stability*

Martien Lamers,[a,b] Frederik Mergaerts,[b] Elien Meuleman,[b] and Rudi Vander Vennet[b]
[a]University of Groningen, Netherlands
[b]Ghent University, Belgium

This paper investigates the transmission of monetary policy to systemic risk of euro-area and U.S. banks between 2008 and 2015. Using market measures of systemic risk and a VAR to obtain monetary policy shocks, we find that accommodative policy generally has a positive effect on bank stability in the euro area but a negative effect in the United States. Different transmission channels are at play: in the euro area the effect works mainly through a stealth recapitalization channel, while in the United States the effect is due to risk-shifting. Moreover, transmission of monetary policy differs across bank business models.

JEL Codes: G21, G32, E52.

1. Introduction

Since the major central banks have embarked on programs of unconventional monetary policy, the potential tradeoff between monetary

*We gratefully acknowledge helpful comments from two anonymous referees, Rafael Repullo (editor), Jef Boeckx, Ferre De Graeve, Olivier De Jonghe, Maite de Sola Perea, Roland Meeks, Jean-Stéphane Mésonnier, Gert Peersman, Raf Wouters, and participants at the 2016 National Bank of Belgium Conference on "The Transmission Mechanism of New and Traditional Instruments of Monetary and Macroprudential Policy." We are also grateful to participants at the EFMA 2017 conference, the 34th Symposium on Money, Banking and Finance, the IFABS 2017 conference, and the EFiC 2017 conference in banking and finance. The authors acknowledge financial support from the Research Foundation - Flanders (FWO), the National Bank of Belgium, and the Hercules Foundation. Corresponding author: Elien Meuleman, Sint-Pietersplein 5, 9000 Gent (Belgium), Elien.Meuleman@ugent.be.

stability and financial stability has received increasing attention from policymakers and academics (Smets 2014; Adrian and Liang 2016). The objective of this paper is to contribute to this topic by focusing on the link between monetary policy and the systemic risk of the banking sector in the euro area and the United States, and hence on a tradeoff between the mandated monetary policy objectives of the central banks and financial stability. While there is evidence on the impact of monetary policy actions on bank lending risk, we argue that it is useful to assess the total impact of various channels of monetary policy transmission on the overall *systemic* risk of banks. From a regulatory and supervisory point of view, it is equally important to identify which banks, or which bank business models, are most exposed to monetary policy measures. To assess the relative importance of different transmission channels, we allow the impact of monetary policy actions to vary across banks. We therefore investigate how actions undertaken by the European Central Bank (ECB) and the Federal Reserve affect systemic risk of European and U.S. banks as perceived by stock markets.

Our analysis consists of three components. First, we obtain monetary policy shocks by estimating a structural vector autoregression (VAR). The monetary policy shock is identified by assuming that its variance increases on days on which there is a monetary policy announcement. This “identification-through-heteroskedasticity” approach, which was first proposed by Rigobon and Sack (2003, 2004), is ultimately based on the assumption that monetary policy announcements dominate other news on these days. Wright (2012) further develops this approach so that it does not require the definition of a specific policy instrument, hence allowing its use in an environment characterized by the zero lower bound and unconventional monetary policy programs. This method displays some advantages over alternative approaches, because it does not require one to either propose an alternative policy instrument, e.g., the size of the central bank balance sheet, or to define the appropriate length of the event window, as is necessary in event studies. We find that the data support our identification strategy, as the standard deviation of the structural monetary shock is found to more than double on announcement days in both the euro area and the United States.

Second, we need a measure that reflects bank systemic risk. As outlined in Bisias et al. (2012), more than thirty competing measures have been developed over the past years, ranging from network analysis to macroeconomic and illiquidity indicators. Some of these measures reflect the aggregate level of systemic risk in the financial system, while others assess the individual bank's systemic risk contribution. In line with most of the literature, we estimate bank systemic risk as contributions to systemic risk using financial market information (see, e.g., Acharya, Engle, and Richardson 2012, Billio et al. 2012, Huang, Zhou, and Zhu 2012, van Oordt and Zhou 2014, and Adrian and Brunnermeier 2016 for different approaches). The use of market data has several advantages. First, it allows us to calculate the cross-sectional, bank-specific, systemic risk contributions when the market is in the tail of its distribution. Second, market data enable a forward-looking assessment of banks and incorporate the expectations of market participants. Third, market data is available at a high frequency, which is not the case for accounting-based measures. This ensures that an unexpected increase in a bank's systemic risk contribution can quickly be identified. In this paper we follow Acharya et al. (2010) and use the long-run marginal expected shortfall (*LRMES*). Over the past years, the *LRMES* has received a lot of attention by academia and regulators, and it has become one of the most commonly used metrics in the literature. In this paper, we complement our measure of bank systemic risk with an additional dimension. In particular, we define bank systemic risk as a bank's vulnerability to systemwide stress as well as the ability of a bank to absorb losses. Although accommodating monetary policy can support bank stability through asset revaluations, the low interest rate environment can also induce risk-taking incentives. To account for this potential tradeoff, we construct a measure that incorporates both dimensions. We use the *LRMES* to capture a bank's vulnerability to large financial shocks and we use the market value of equity to capture the loss-absorbing capacity of the bank. This approach allows us to assess the tradeoff between increased bank vulnerability versus better shock absorbency capacity of banks caused by a monetary policy shock.

Finally, we assess the impact of monetary shocks on bank systemic risk using a panel regression framework. By interacting the shock with a set of bank characteristics capturing the bank's business model, we can furthermore evaluate the relative importance of different transmission channels.

Our results indicate that expansionary monetary policy shocks affect bank systemic risk through different transmission channels in the euro area and the United States. First, consistent with Lambert and Ueda (2014), we find evidence that accommodative monetary policy may delay balance sheet repair in the banking sector by allowing banks more room to postpone recognizing bad loans. Second, our results are in line with the existence of a stealth recapitalization channel, both in the euro area and in the United States. Moreover, our findings indicate that the negative impact of a forbearance channel on bank systemic risk for the peripheral euro-area banks is counteracted by the increased value of the bank's net worth. For the United States we find evidence for the existence of a funding risk channel and a risk-shifting effect, indicating that highly capitalized banks and deposit-funded banks tend to increase systemic risk more than other banks. In general, our results emphasize the importance of the bank business model in the transmission of monetary policy to bank systemic risk.

This paper is related to a growing literature investigating the effect of monetary policy on financial stability, and specifically bank risk-taking. These papers often use detailed loan-level data to check whether banks increase the risk of new loans in response to a decrease of interest rates (Paligorova and Santos 2012; Jiménez et al. 2014; Ioannidou, Ongena, and Peydró 2015; Dell'Ariccia, Laeven, and Suarez 2017).[1] We contribute to this literature by analyzing the transmission of monetary policy shocks to overall bank *systemic* risk, using stock-market-based measures of bank risk as in Altunbas, Gambacorta, and Marques-Ibanez (2014). We furthermore argue that the impact of monetary policy interventions on banks may differ according to the business model following, among others, Brissimis and Delis (2010), Delis and Kouretas (2011), and Ricci (2015). Therefore we assess the importance of a set of bank characteristics that have been shown to determine the long-term profitability and

[1]Maddaloni and Peydró (2013) and Buch, Eickmeier, and Prieto (2014) instead use survey data from the ECB's Bank Lending Survey and the Federal Reserve's Survey of Terms of Business Lending, respectively.

risk profile of the banks (Mergaerts and Vander Vennet 2016) in the transmission of monetary policy to systemic risk.

The remainder of the paper is structured in the following way. In section 2, we discuss the transmission of monetary policy to bank systemic risk and the role of different bank characteristics, resulting in several testable hypotheses. In sections 3 and 4, we provide details on the methodology and data. In section 5 we discuss the results of our estimations and provide an analysis of the impact of monetary policy on financial stability. Section 6 concludes the paper with some policy considerations.

2. Monetary Policy and Bank Systemic Risk

In this paper we investigate whether accommodative monetary policy promotes or deteriorates financial stability. Central bank interventions may ease financial conditions but may also affect risk-taking incentives. A negative impact would imply a tradeoff between stimulating the economy and avoiding the buildup of vulnerabilities within the financial system.

2.1 The Transmission of Monetary Policy to Bank Stability

We identify four channels through which monetary policy interventions can affect bank stability, namely (i) the net interest margin channel, (ii) the recapitalization channel, (iii) the funding risk channel, and (iv) the forbearance channel. First, an expansionary monetary policy action feeds through to bank profitability, as falling short-term interest rates are typically associated with increasing net interest margins. A rising net interest margin may affect banks' risk-taking incentives by increasing their payoff of monitoring borrowers (see, e.g., Dell'Ariccia, Laeven, and Marquez 2014). We expect that both improved profitability and lower risk-taking will translate into a higher stock market valuation and lower risk. However, to the extent that the continuous decline of long-term interest rates decreases banks' net interest margins, a further loosening of monetary policy may affect bank profitability negatively (Borio, Gambacorta, and Hofmann 2015; Busch and Memmel 2015) and increase banks' risk-taking, e.g., because of search for yield (Rajan 2005;

Chodorow-Reich 2014). Ex ante, it is unclear which of these effects dominates.

Second, expansionary monetary policy interventions tend to boost asset prices and can therefore be considered what Brunnermeier and Sannikov (2014) have labeled a stealth recapitalization channel, i.e., the increase of the value of (legacy) assets leading to a higher net worth of the bank. If investors consider the revaluation of bank assets as sustainable, it may lead to lower bank systemic risk. A rising value of collateral pledged to secure bank loans may furthermore reduce the loss given default of bank portfolios, increasing their value as well.

Third, we distinguish a funding risk channel. In both the euro area and the United States the start of the financial crisis in 2008 was characterized by problems in wholesale funding markets. In response, monetary authorities have undertaken actions to improve liquidity in the banking sector. The alleviation of funding risk may have contributed to lower funding costs, and hence higher bank profitability, and a decline of banks' vulnerability to further financial shocks. Given sufficient demand for credit, central bank liquidity provision may furthermore improve banks' lending capacity (Boeckx, Dossche, and Peersman 2017) and thereby increase profitability. These effects should translate into a decrease of systemic risk.

Finally, by improving banks' capitalization and lowering their funding risk, monetary policy actions have the potential to reduce bank systemic risk. However, improving profitability, net worth, and funding stability may also allow banks to postpone cleaning up their balance sheets by writing off non-performing loans (Peek and Rosengren 2005; Lambert and Ueda 2014; Acharya et al. 2019). Such a forbearance channel may increase uncertainty about potential future write-offs and hence depress market values and increase bank systemic risk.

2.2 Monetary Policy Transmission and Bank Heterogeneity

While monetary policy interventions are likely to affect bank systemic risk, each bank may be affected differently conditional on bank business model characteristics such as asset, funding, capital, and income structure.

A bank's asset structure, which encompasses both the composition and the quality of assets, may affect the transmission of monetary policy shocks to bank systemic risk through the net interest margin, the stealth recapitalization channel, and the forbearance channel. First, we hypothesize that banks with a higher loans-to-assets ratio react more strongly to monetary policy shocks, because they are more sensitive to changes in the net interest margin. However, the sign of this relationship remains an empirical question, as the impact of expansionary monetary policy on the net interest margin is ambiguous. Second, we expect that increasing collateral values and the improvement of economic and financial conditions is especially beneficial for banks with a riskier asset structure. Banks characterized by a loan-oriented asset composition, finally, may have stronger incentives to use the access to central bank liquidity to delay recognizing bad loans. According to this forbearance channel, markets may consider banks with higher loan ratios to become more systemically risky and less profitable following an expansionary monetary policy shock, especially if there are doubts about the loan quality.[2] With respect to asset risk, we expect that increasing asset prices and decreasing risk premiums through the stealth recapitalization channel may be especially beneficial for banks with a riskier asset structure.

The extent to which the net interest margin channel affects the pass-through of monetary policy interventions to bank systemic risk furthermore depends on a bank's income structure. A bank that relies more on activities that generate net interest income may benefit more from monetary policies that lower short-term interest rates, while it may face declining profitability when long-term rates decrease as well, e.g., as a result of central bank asset purchases.

The impact of a bank's funding structure on the transmission of monetary policy shocks operates mainly through the funding risk channel. We expect that banks that rely more on wholesale

[2]Such doubts may be stronger for banks in euro-area periphery countries. For instance, in Italy non-performing loans have tripled during our sample period, rising to a proportion of 18 percent of total outstanding loans by December 2015. Garrido, Kopp, and Weber (2016) suggest that write-offs may have taken too long because of economic and legal obstacles.

funding may benefit more from accommodative monetary policy actions because access to central bank funding can decrease a bank's vulnerability to liquidity shocks by reducing its dependence on more volatile wholesale markets. Moreover, a high reliance on retail funding may weaken private monitoring because customer deposits are typically covered by deposit insurance. This feature may intensify agency problems (see, e.g., Demirgüç-Kunt and Detragiache 2002, and Demirgüç-Kunt and Huizinga 2004). Mamatzakis and Bermpei (2016) indeed show that the negative impact of the Federal Reserve's expansionary policies is stronger for banks characterized by a high deposit ratio (see also Yin and Yang 2013). For the euro area, Ricci (2015) provides event-study evidence that, in response to an expansionary monetary policy shock, stock prices of banks with a higher deposit ratio rise less than those of banks that rely more on wholesale funding.

Concerning the impact of a bank's capital ratio on the effect of monetary policy shocks, the banking literature advances divergent theories. On the one hand, poorly capitalized banks stand to gain most from asset revaluation, especially if they are exposed to a high level of distressed assets. Brunnermeier and Sannikov (2014) therefore use the term stealth recapitalization to describe the impact of improving asset values. Furthermore, because they rely more on debt funding, their profitability is more responsive to monetary policy shocks that affect short- and long-term interest rates (Madura and Schnusenberg 2000; Yin and Yang 2013; Ricci 2015). On the one hand, depressed net interest margins can damage a bank's profitability and thereby increase moral hazard and risk-taking incentives, particularly for banks with lower capital ratios. The search-for-yield hypothesis implies that banks increase risk-taking when interest rates decline and that the strength of this effect increases with the prevalence of agency problems. On the other hand, risk shifting suggests that, as far as expansionary monetary policy increases banks' net interest margins, the incentives to monitor are strengthened and should hence result in lower risk (Dell'Ariccia, Laeven, and Marquez 2014). This effect is expected to be stronger for banks with low capital ratios that have more scope to reduce risk, because more highly capitalized banks' monitoring incentives are less dependent on the stance of monetary policy. De Nicolò et al. (2010) and Dell'Ariccia, Laeven, and Suarez (2017) provide evidence supporting the existence of a risk-shifting effect in the United States. In the next sections we investigate the relative strength of these hypotheses.

3. Methodology

In this section we discuss the three components of our methodology. In section 3.1 we describe the estimation of the monetary policy shocks and analyze the results of applying our identification strategy. In section 3.2 we define bank systemic risk and the set of variables we use to measure it. Finally, in section 3.3, we present the panel setup we use to assess the impact of monetary policy actions on bank systemic risk.

3.1 Monetary Policy Shock

3.1.1 Model

We estimate a time series of the exogenous monetary policy shock by modeling a set of relevant financial variables in a structural VAR model at daily frequency. Our identification strategy, which was first proposed by Rigobon and Sack (2003, 2004) and adapted by Wright (2012), is based on the assumption that the structural monetary policy shock is more volatile on days on which there is a monetary policy announcement (the specific set of days must be determined a priori). As a result, the volatility of any other structural shocks and the transmission of the shock within the model are assumed to be time invariant.[3] Other studies employing this "identification-through-heteroskedasticity" methodology to identify the effects of structural monetary policy shocks include, for example, Gilchrist and Zakrajsek (2013), Rogers, Scotti, and Wright (2014), and Arai (2017).

Estimating the monetary policy shock this way has some advantages over alternative approaches. First, while event studies are often

[3]Note that this time invariance is a necessary condition for identification, but it excludes the possibility to examine and compare the impacts of different policies, e.g., conventional interest rate changes and unconventional asset purchasing programs.

used to identify the impact of monetary policy announcements on bond yields and financial markets (e.g., Taylor and Williams 2009, Gagnon et al. 2011, Joyce et al. 2011, Krishnamurthy and Vissing-Jorgensen 2011, Swanson 2011, and Neely 2015), they may be susceptible to simultaneity bias as a consequence of concurrent financial shocks that influence monetary policy as well as asset prices. To circumvent this problem, some event studies use an intraday event window and effectively assume that the variance of the other shocks within this window is zero (Joyce and Tong 2012). Gilchrist and Zakrajsek (2013) document that event-study approaches therefore underestimate the impact of monetary policy announcements. Event studies moreover require full adjustment of asset prices within the event window. However, because unconventional monetary policy actions were mostly untested in the euro area and the United States, adjustment periods may be longer and would hence require longer event windows (Meaning and Zhu 2011; Neely 2015). Finally, some announcements may have been largely anticipated, leading to limited adjustments of asset prices and bond yields within the event window. In our model we do not assume the absence of other shocks on announcement days, but only that they become relatively less important than the monetary policy shock. We can furthermore estimate the monetary policy shock on non-announcement days to pick up anticipation of monetary policy actions.

Second, most other approaches require the definition of a policy instrument. However, using the short-term interest rate may be problematic due to the zero lower bound. Alternative measures have therefore been proposed, including the size of the central bank balance sheet (Gambacorta, Hofmann, and Peersman 2014; Garcia Pascual and Wieladek 2016; Boeckx, Dossche, and Peersman 2017), the interbank interest rate (Gambacorta and Shin 2018), long-term interest rates (Chen et al. 2012, 2016; Gilchrist, Lopez-Salido, and Zakrajsek 2015) or the term spread (Baumeister and Benati 2013).[4] The identification-through-heteroskedasticity approach allows us to avoid having to choose a specific policy instrument.

[4]Another approach consists of estimating a latent policy stance, such as a shadow policy rate (Lombardi and Zhu 2014) or a latent propensity for quantitative easing (Meinusch and Tillmann 2016).

The identification of the monetary policy shocks is based on the following structural VAR model:

$$Y_t = A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + R\nu_t, \tag{1}$$

where Y_t is an N-dimensional vector of endogenous variables $(t = 1, \ldots, T)$, ν_t is an N-dimensional vector of orthogonal structural innovations with mean zero, and $A_1, \ldots, A_p$ and R are $N \times N$ time-invariant parameter matrices. The reduced-form residuals corresponding to this structural model are given by the relationship $\varepsilon_t = R\nu_t$. In this model we assume that the first[5] structural shock changes on announcement days, while the other structural innovations are homoskedastic, so that

$$Var(\nu_t) = \Omega_t = \begin{cases} \Omega^{(0)} = (\omega_1, \omega_2, \ldots, \omega_N) & \textit{if no announcement} \\ \Omega^{(1)} = (\omega_1^*, \omega_2, \ldots, \omega_N) & \textit{if announcement.} \end{cases} \tag{2}$$

It can be shown that, as long as the covariance matrix of the reduced-form errors V_t changes on announcement days, these assumptions suffice to uniquely identify the first column of R and the structural monetary policy shock apart from their scale and sign. In our setup we normalize the monetary policy shock by fixing the response on impact of one of the included variables to a unit monetary policy shock.

3.1.2 Estimation and Testing

To estimate the model defined by equations (1) and (2), we follow the iterative estimation procedure of Lanne and Lütkepohl (2008). It consists of the following steps:

(i) The reduced-form VAR model in (1) is estimated using OLS, i.e., under the assumption of homoskedasticity. The estimated residuals are used to construct estimates of the covariance matrices V_t. Defining D_t as a dummy variable that takes

[5] Note that ordering the monetary policy shock first is purely for convenience and does not affect the model.

value 1 on announcement days and 0 on other days, we can write

$$\tilde{V}_t = \begin{cases} \frac{\sum_{t=1}^{T}(1-D_t)\hat{\varepsilon}_t\hat{\varepsilon}_t^{'}}{T-\sum_{t=1}^{T}D_t} & \textit{if } D_t = 0 \\ \frac{\sum_{t=1}^{T}D_t\hat{\varepsilon}_t\hat{\varepsilon}_t^{'}}{\sum_{t=1}^{T}D_t} & \textit{if } D_t = 1. \end{cases} \tag{3}$$

(ii) Using our estimates for V_t, we minimize the following loss function to obtain the estimates for R and Ω_t:

$$\left(\hat{R}, \hat{\Omega}_t\right) = \arg\min_{\hat{R},\hat{\Omega}_t} \left\{ - \left(\sum_{t=1}^{T} \log |R\Omega_t R'| + \left[\tilde{V}_t \left(R\Omega_t R'\right)^{-1} \right] \right) \right\}. \tag{4}$$

(iii) The estimates $\hat{R}$ and $\hat{\Omega}_t$ can then be used to reestimate the VAR model in (1) by GLS. This step again results in estimates for the reduced-form residuals, which are used to construct new estimates of V_t.

Steps (ii) and (iii) are iterated until convergence. Using $\hat{R}$ and the GLS estimates of the reduced-form errors, we can then trace out the structural monetary policy shock.

Since the identification strategy relies on the presence of a heteroskedastic monetary policy shock, it is important to test whether our model indeed supports a rejection of homoskedastic errors. The following hypothesis is therefore of interest:

$$\begin{cases} H_0 : \omega_1 = \omega_1^* \\ H_1 : \omega_1 \neq \omega_1^*. \end{cases} \tag{5}$$

In other words, we compare the homoskedastic model under the null hypothesis to a model in which we relax the restriction on one parameter, i.e., we do not impose $\omega_1^* = \omega_1$. Our use of (Q)ML estimators enables us to perform a likelihood-ratio test[6] to examine this hypothesis.

[6] In the framework of this model these tests will retain their standard asymptotic properties. We refer to Lanne and Lütkepohl (2008) for a more complete discussion of their statistical properties.

Table 1. The Financial Market Variables Used in the VAR Model to Obtain the Monetary Policy Shock

Euro Area	United States
Germany Ten-Year Bond Rate	U.S. Trasury Ten-Year Rate
Expected Five-Year Inflation	Expected Five-Year Inflation
Datastream EMU Broad Market Index	S&P 500
VSTOXX	VIX
Spanish Five-Year CDS Spread	

Notes: Inflation expectations are based on inflation swap rates. Data are obtained from Datastream.

3.1.3 Results

To estimate the VAR we use a set of variables that should capture the pass-through of monetary policy to the financial sector. Hence, following Rogers, Scotti, and Wright (2014), we select those variables that are expected to respond most to a monetary policy shock. For both the euro area and the United States we include a long-term interest rate, a measure for inflation expectations, and the return and implied volatility of a broad stock market index. Because the sovereign debt crisis has forced the ECB to implement unconventional policy actions aimed at restoring the transmission of monetary policy, we furthermore include a sovereign stress indicator in the euro-area VAR, specifically the Spanish five-year credit default swap (CDS) spread.[7] Details of the specific variables can be found in table 1. A VAR of order 2 is estimated over a sample period from October 1, 2008 to December 31, 2015.[8]

[7]The rationale for using the Spanish five-year CDS spread is that Spain is the prototypical euro-area periphery country which was hit by the banking crisis, a real estate crisis, and by the sovereign crisis and it was not rescued with loans from the European Financial Stability Facility/European Stability Mechanism (unlike, e.g., Portugal, Ireland, or Greece). However, as a robustness check, we also experimented with other sovereign stress indicators: the five-year CDS spreads of Italy and France, an index of European five-year sovereign CDS spreads, and an index based on the five-year CDS spreads of Spain, Portugal, Italy, and Ireland. Our findings do not appear to be driven by the choice of the sovereign stress indicator.

[8]In unreported regressions we find that the results are robust to different choices of the VAR order.

The identification of the monetary policy shock requires a set of announcement dates for both central banks. For the ECB we include all announcements pertaining to interest rates, asset purchase programs, long-term refinancing operations (LTROs), central bank funding conditions, forward guidance, and new swap arrangements with other central banks.[9] Federal Reserve announcement dates include interest rate decisions as well as announcements regarding asset purchase programs, lending facility conditions, forward guidance, and swap agreements.[10] This selection procedure leads to a set of ninety-three announcements in the euro area and seventy-four in the United States.[11] While the specific choice of announcement dates is of course open for debate, we find that our results are robust to different sets of announcement dates.[12]

[9]Interest rate announcements also include the ECB Governing Council's decisions to leave the interest rate unchanged so that all Governing Council meetings are present in the set of announcement dates. Asset purchase program announcements relate to the three covered bond purchase programs, the ABS purchase program, the (sterilized) securities markets program, the outright monetary transactions, and the public-sector purchase program. The corporate-sector purchase program was announced in April 2016 and is therefore not part of the sample. With central bank funding conditions we refer to changes in tendering procedures such as fixed-rate full allotment and collateral requirements.

[10]In line with our choice of announcement dates of the ECB, we include all announcements following Federal Open Market Committee (FOMC) meetings, even if they only decide to keep the interest rate unchanged. Asset purchase programs include the three quantitative easing programs and the (sterilized) Operation Twist. Lending facility conditions refer to both the institution and closing of specific lending facilities such as the Term Auction Facility and the Term ABS Loan Facility, among others.

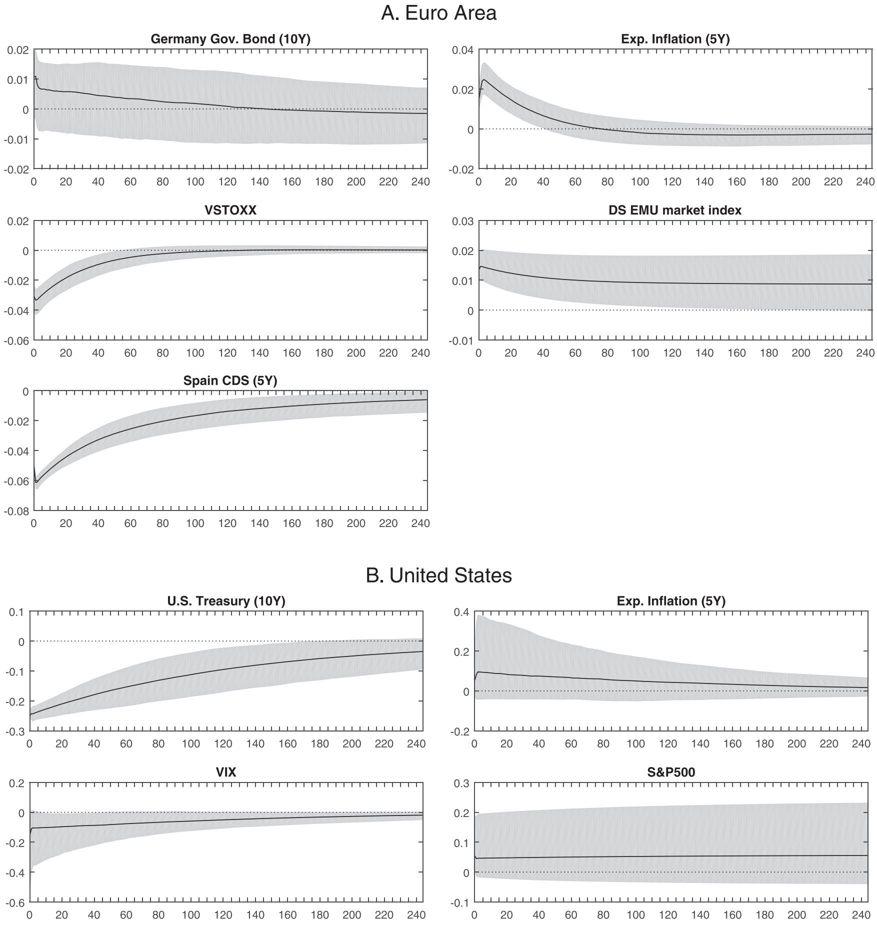
[11]Details on the specific dates and announcements can be found in the appendix.

[12]As a robustness check, we experiment with different choices for the set of announcement dates. For the euro area, we find that a more strict choice of thirty-six policy dates, leaving out the ECB Governing Council meetings that produced no interest rate changes or unconventional monetary policy actions, leads to an increase of the variance change of the monetary policy shock on announcement days, yielding a variance multiplier of 11.52. For the United States, a more strict choice of fifty policy dates, leaving out the FOMC meetings that produced no interest rate changes or unconventional monetary policy (UMP) actions, leads to an increase of the variance change of the monetary policy shock on announcement days, yielding a variance multiplier of 7.39. However, it does not affect any of our further results, as the correlation with the baseline shock remains 0.99 in both cases.

The estimation of the model yields variance multipliers of 4.91 and 5.39 for the euro area and the United States, respectively, implying that the standard deviation of the monetary shock is more than twice as high on announcement days in both regions. A likelihood-ratio test for the hypothesis test (equation (5)) results in test statistics of 177.55 for the euro area and 169.19 for the United States, so that the null hypothesis of equal variance on both announcement and non-announcement days is strongly rejected by the data. Hence these tests provide support to our identification strategy. In figure 1 we present the impulse response functions of the variables to a unit monetary policy shock. Our identification strategy is not able to identify the sign and specific scale of the shock. We therefore define a unit expansionary monetary policy shock as a shock that decreases the Spanish five-year CDS spread by 5 percent upon impact for the euro area and as a shock that decreases the ten-year Treasury-bill yield by 25 basis points for the United States, in line with Wright (2012) and Rogers, Scotti, and Wright (2014). In the euro area (figure 1A) we find that an expansionary monetary policy shock increases long-term inflation expectations and the value of the broad stock market index, while decreasing marketwide implied volatility (VSTOXX). Although the negative contemporaneous impact on sovereign stress is a consequence of our identification strategy, the effect remains significantly negative across the whole horizon. We do not observe a significant impact on the yield of the long-term safe asset, possibly due to a flight-to-safety effect in which monetary easing lowers the demand for safe assets, such as German bunds, by decreasing the risk of stressed sovereign bonds (see also Altavilla, Giannone, and Lenza 2014 and Rogers, Scotti, and Wright 2014). For the United States the effects are very similar: we observe a positive effect on long-term inflation expectations and the value of the S&P 500 stock market index and a negative effect on marketwide implied volatility (VIX). As expected, for the United States the effect of an expansionary monetary policy shock on the long-term safe asset yield is significantly negative over the entire horizon.

As a check of the soundness of our methodology and in line with Boeckx, Dossche, and Peersman (2017), we plot the time series of the cumulative monetary policy shock for both the euro area and the United States in figures 2 and 3, respectively. A sequence of positive monetary policy shocks indicates that monetary policy is

Figure 1. Impulse Response Function of the Variables to a Unit Monetary Policy Shock



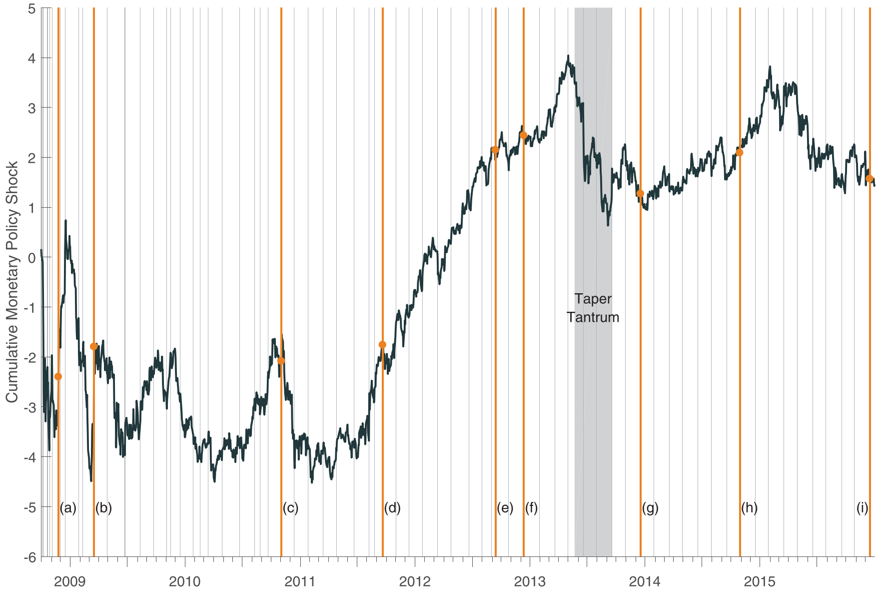
Notes: Gray areas represent 68 percent confidence intervals that are obtained through a stationary bootstrap with expected block length 10 for non-announcement days. Announcement-day residuals are bootstrapped separately. The horizontal axis represents the horizon of the impulse response function in working days, i.e., the IRFs are plotted for a horizon of 240 days.

becoming more expansionary and therefore the cumulative series reflects the monetary policy stance with respect to the prevailing economic environment and expectations of financial markets. As a consequence, a drop in the series can reflect a tightening of

Figure 2. Time Series of the Cumulative Monetary Policy Shocks for the Euro Area

Notes: An increase of the cumulative shock series reflects an expansionary monetary policy announcement. Vertical lines represent the set of announcement dates used in the estimation of the shock. We highlight some of these announcement dates: (a) the ECB starts its first covered bond purchase program (CBPP1) and announces a one-year LTRO; (b) the ECB announces its Securities Markets Program; (c) the ECB increases its MRO interest rate; (d) the ECB activates the SMP for Italy and Spain; (e) the ECB announces its second covered bond purchase program (CBPP2) and the provision of two additional one-year LTROs; (f) the ECB announces the provision of two LTROs with a maturity of three years; (g) ECB President Mario Draghi states that the ECB "is ready to do whatever it takes to preserve the euro"; (h) introduction of the Outright Monetary Purchases (OMT) program; (i) the ECB offers forward guidance by stating that interest rates will "remain at present or lower levels for an extended period of time"; (j) the ECB lowers the deposit facility rate to −0.10 percent and announces the start of an ABS purchase program (ABSPP) and a series of targeted LTROs; (k) ECB President Mario Draghi states that the ECB "will use all the available instruments needed to ensure price stability over the medium term," which is interpreted as hinting at QE; (l) the ECB starts its third covered bond purchase program (CBPP3); (m) the ECB announces it will start buying public-sector securities (EUR 60 billion per month until September 2016); (n) the ECB extends its asset purchase program to March 2017.

Figure 3. Time Series of the Cumulative Monetary Policy Shocks for the United States



Notes: An increase of the cumulative shock series reflects an expansionary monetary policy announcement. Vertical lines represent the set of announcement dates used in the estimation of the shock. We highlight some of these announcement dates: (a) the Fed creates the Term ABS Loan Facility (TALF) and starts purchasing Agency MBS and debt (QE1); (b) the Fed expands its purchases of Agency MBS and debt and starts buying longer-term Treasury securities; (c) the Fed announces that it will again start buying longer-term Treasury securities (QE2); (d) the Fed announces that it will extend the average maturity of its securities holdings ("Operation Twist"); (e) the Fed decides to start purchasing Agency MBS (QE3); (f) the Fed again starts purchasing additional longer-term Treasury securities after the conclusion of its program to extend the average maturity of its securities holdings; (g) the monthly purchases of Agency MBS and Treasury securities are reduced for the first time; (h) the Agency MBS and Treasury purchase programs are discontinued and the Fed signals that a rate increase is possible in the near future "if incoming information indicates faster progress toward the Committee's employment and inflation objectives than the Committee now expects"; (i) the Fed increases the federal funds rate. The period commonly known as the taper tantrum is indicated by a shaded area.

monetary policy but also the lack of monetary action or even that there were expansionary announcements that failed to live up to financial market expectations. The figures show that the shocks are able to capture important monetary policy announcements, as well as the anticipation of some measures. For the euro area, the one-year LTRO/CBPP1 announcement in May 2009 and the Securities Market Program (SMP) announcement in May 2010 are among the largest expansionary daily shocks and can therefore be considered surprises to financial markets. On the other hand, the OMT (outright monetary transactions) announcement of September 2012 appears to have been largely anticipated following the speech by ECB President Mario Draghi in which he alluded to the implementation of additional unconventional monetary policy measures. For the United States, the announcement of the first quantitative easing program (QE1) is identified as the largest shock, and hence the largest surprise to financial markets, while the small shocks on the QE2 and QE3 announcement days suggest that these programs were largely anticipated. Further in line with anticipation, the cumulative monetary policy shock reflects the buildup of the accommodative monetary policy stance before the announcements of the QE2, Operation Twist, and QE3 programs. The cumulative shock gradually decreases following the taper announcement in May 2013. As such, the inspection of the cumulative monetary policy shock series further supports the appropriateness of our identification strategy.

3.2 Bank Systemic Risk

Now that we have obtained a measure that reflects exogenous monetary policy shocks, we turn to the measurement of bank systemic risk. In line with Acharya et al. (2010), Acharya, Engle, and Richardson (2012), and Adrian and Brunnermeier (2016), we base our measure of bank systemic risk on financial market data. The definition of bank systemic risk used in this paper encompasses two complementary dimensions. First, an increase in systemic risk indicates that a bank becomes more vulnerable to adverse shocks within the financial system as a whole. If a bank is prone to suffer extreme losses during an industry-wide stress event, its activities are less likely to be taken up by other actors within the financial sector, because their ability to do so is also severely impaired. In addition, a potential recapitalization to allow the bank to continue its activities is both difficult and costly during a systemic event due to the entire banking system being undercapitalized. However, if the bank is able to bear severe losses, it can continue its activities without requiring recapitalization. Hence, bank capital is a crucial second dimension of systemic risk.

We estimate the first dimension, a bank's vulnerability to large financial shocks, using the long-run marginal expected shortfall (*LRMES*) following Acharya et al. (2010). The *LRMES* is defined as the expected loss of a bank's market value when a large downturn, or crisis, occurs. For our analysis we use the proxied *LRMES* measure of the NYU Stern Volatility Institute:

$$LRMES_{i,t} = 1 - \exp\left\{\log\left(1 - C\right) \times \beta_{i,t}\right\},$$

where $LRMES_{i,t}$ is the long-run marginal expected shortfall for bank i at time t, C is the threshold for defining a crisis, and $\beta_{i,t}$ is the time-varying beta coefficient of the bank. In line with Acharya, Engle, and Richardson (2012) and the NYU Stern Volatility Institute, the threshold that defines a crisis is set at a 40 percent loss in the relevant market index over a six-month time period.[13] To construct the series of time-varying correlations yielding the beta estimates $\beta_{i,t}$, we use an asymmetric dynamic conditional correlation (ADCC) model as in Cappiello, Engle, and Sheppard (2006). The ADCC model is estimated over the period January 2008 to December 2015.

The second component, the perception of the stock market of a bank's capacity to absorb unexpected losses, is reflected by the total market value of its equity (MV). Finally, to analyze systemic risk, we need to consider the potential tradeoff between systemic vulnerability and capitalization. We therefore combine the two components, which yields our measure of bank systemic risk, the stressed market value (SMV).

$$SMV_{i,t} = (1 - LRMES_{i,t}) \times MV_{i,t}$$

SMV is the capital the bank is expected to end up with in the event of a large adverse shock to the financial system. This variable can be considered as the market-based equivalent of the accounting-based simulated stress-test exercises that are currently being undertaken

[13]Our results were not affected by alternative choices of the six-month crisis threshold.

on a regular basis by bank supervisors in Europe, the United States, and other jurisdictions.[14] Because monetary policy affects the market's perception of the value of a bank's assets and its vulnerability to stress events, *SMV* is likely to react immediately to announcements regarding monetary policy. Finally, *SMV* can capture a potential risk–return tradeoff if *LRMES* and *MV* react in different ways. A monetary policy action that lowers the interest rate may, for instance, increase a bank's market capitalization through a higher net interest margin but at the same time increase risk-taking. By analyzing both components we can quantify this potential tradeoff.

3.3 Transmission of Monetary Policy and Bank Heterogeneity

In the last step we look at the impact of monetary policy on the market's perception of banks' systemic risk. As the impact is likely to be different for different types of banks, we estimate a panel model in which we allow for bank heterogeneity. Concretely, we estimate the following panel model using variables at monthly frequency:

$$Y_{i,t} = \alpha_i + \left(\beta_0 + \sum_{k=1}^{K} \beta_k BM_{k,i,t}\right) \times Shock_t + \sum_{k=1}^{K} \gamma_k BM_{k,i,t} + \varepsilon_{i,t}, \tag{6}$$

where $Y_{i,t}$ represents one of the dependent variables, $BM_{i,t}$ is a vector of business model characteristics, and $Shock_t$ is the value of the monetary policy shock in month t. Using this approach, we allow the impact of the monetary policy shock to vary both over banks and over time, conditioning the effect on the bank's business model.

Our main dependent variable is the monthly percentage change of the stressed market value ΔSMV as a measure of a bank's systemic risk. We also use as dependent variables the components of the change of *SMV*, i.e., changes in *LRMES* and in market valuation. We focus on the immediate changes in bank systemic risk due to monetary policy that are solely driven by the changing market appraisal of the bank. However, *MV* is also influenced by dividend payouts or changes in the outstanding number of shares, e.g., because of

[14] The relationship between marginal expected shortfall and stress-testing scenarios is documented in more detail by Acharya, Engle, and Pierret (2014).

new issuance or share buybacks. We therefore measure MV using a total return index so that ΔMV equals the monthly holding period return.

The business model characteristics in BM are derived from the banks' balance sheets and the income statements and capture the asset, liability, capital, and income structure of the banks. However, while our panel analysis is conducted on monthly frequency, accounting data are only available on an annual basis in the euro area and on a quarterly basis in the United States. To tackle this issue, we replace the value of the business model variables with their last known value of the previous month; e.g., the value reported for the end of December 2014 is used for the entire year of 2015 in Europe and for the first quarter of 2015 in the United States. By using the last known value prior to month t, we also avoid endogeneity issues, as systemic risk and market valuation may also influence a bank's business model decisions. Finally, the dependent variables $\Delta LRMES$, ΔMV, and ΔSMV and the monetary policy shock are aggregated from daily to monthly frequency so that they reflect the changes of systemic risk and the monetary policy stance over the entire month. Hence, the changes in the systemic risk measures are computed using end-of-month values, while the monthly monetary policy shock is calculated as the sum of the daily *absolute* shocks within each month.

4. Data

To conduct our analysis we require both financial market and accounting data for a set of listed euro-area and U.S. banks. With respect to the euro area, we obtain annual balance sheet and income statement data from Bankscope and daily stock return data from Datastream, which are linked based on the international securities identification number (ISIN) codes. We limit the sample to banks of which the Bankscope specialization is either bank holding company, commercial bank, cooperative bank, investment bank, or real estate and mortgage bank. We furthermore exclude financial holding companies that lack banking activity of their own and the listed regional branches of the French bank Crédit Agricole. For the U.S. sample we collect quarterly balance sheet and income statement data from the FR Y-9C reports and daily stock return data from the Center for Research in Security Prices (CRSP) on all listed U.S. bank holding companies. The financial market data is linked to the accounting-based data using the identifier match provided by the Federal Reserve Bank of New York.[15] Finally, because the *LRMES* is estimated on a daily frequency, we require that the stocks in our analysis are liquidly traded. In the euro area we therefore impose that at least 75 percent of returns are non-zero during the sample period, while for U.S. banks we require that there should be trading activity on at least 85 percent of trading days.[16] After the application of this data selection procedure, we end up with sixty-three euro-area banks resulting in 4,502 observations and 438 U.S. bank holding companies for a total of 24,508 monthly observations.

On the basis of the accounting data, we construct a set of business model variables to capture the asset, liability, capital, and income structure of the banks. We also include bank size, measured by total assets, as a control variable. The more granular nature of the (publicly available) FR Y-9C reports allows us to define a more detailed set of variables for U.S. banks. In table 2 we present descriptive statistics for both the dependent and the independent variables. Note that all variables have been winsorized per month to control for potential noise in the estimation induced by outliers.[17]

As discussed in section 3.3, we model the heterogeneous impact of monetary policy shocks on bank systemic risk using a set of business model variables that capture a bank's asset, funding, capital, and income structure. We measure a bank's asset structure by

[15]We control for business model changes through mergers by creating a new bank identifier when a bank's size increases by more than 50 percent (otherwise it is classified as an acquisition). Similarly, we also create a new identifier when the bank's size decreases by more than 50 percent in one quarter to control for large divestments that may fundamentally affect a bank's business model. Finally, we make sure that we have continuous data on each bank by creating a new identifier whenever there is a gap in the bank-specific time series.

[16]The threshold is put lower for the euro area due to the lower available number of listed banks and hence the need to maintain the representativeness of the sample, especially with respect to subsample analysis.

[17]The U.S. data are winsorized at the percent level, while for the euro-area banks we winsorize the highest and the lowest value of each variable in each month. This difference in winsorizing procedures is a consequence of the lower number of banks in the euro area.

Table 2. Descriptive Statistics

	Euro Area					United States				
	Mean	**SD**	**Min.**	**Med.**	**Max.**	**Mean**	**SD**	**Min.**	**Med.**	**Max.**
Loans to Earning Assets	0.63	0.19	0.12	0.67	0.88	0.72	0.15	0.07	0.74	0.98
Cons. Loans to Earning Assets						0.04	0.06	0.00	0.02	0.44
RE Loans to Earning Assets						0.54	0.18	0.00	0.56	0.93
Bus. Loans to Earning Assets						0.15	0.10	0.00	0.13	0.69
Non-perf. Loans to Loans	0.09	0.08	0.00	0.06	0.41	0.03	0.03	0.00	0.03	0.21
RWA to Earning Assets	0.59	0.19	0.20	0.59	1.11	0.81	0.12	0.42	0.81	1.18
Size	18.04	1.83	14.14	18.15	21.47	10.60	1.59	8.45	10.19	16.58
Deposits to Liabilities	0.48	0.17	0.06	0.48	0.91	0.85	0.13	0.09	0.88	0.99
Share of Core Funding						0.70	0.17	0.06	0.74	0.97
NSFR						1.09	0.15	0.57	1.08	1.80
Equity to Assets	0.06	0.02	0.01	0.07	0.12	0.10	0.03	0.00	0.10	0.23
Share of Non-interest Income	0.37	0.15	0.03	0.35	0.86	0.26	0.16	0.01	0.23	0.97
Share of Fee Income						0.06	0.04	0.00	0.06	0.20
Share of Fiduciary Income						0.03	0.06	0.00	0.01	0.50
Share of Trading Income						0.01	0.03	0.00	0.00	0.33
Share of Insurance Income						0.01	0.03	0.00	0.00	0.17
$\Delta LRMES$	0.00	0.11	−0.54	0.00	0.48	0.00	0.12	−0.67	0.00	0.53
ΔMV	0.00	0.14	−0.88	−0.01	1.43	0.01	0.12	−0.69	0.01	1.35
ΔSMV	0.03	0.32	−0.91	−0.01	5.76	0.03	0.29	−0.87	0.00	2.70
Observations	4,502					24,508				

Note: Data are obtained from Bankscope and Datastream for the euro area and from the FR Y-9C reports and CRSP for the United States.

defining a set of variables that capture the composition of earning assets (the loan ratio), the risk of earning assets (the ratio of risk-weighted assets to total assets, or RWA density), and the quality of the loan portfolio (the proportion of non-performing loans in total loans). We use the ratio of customer deposits to total liabilities and an unweighted capital ratio, i.e., the ratio of total equity to total assets, to capture banks' funding and capital structures, respectively. As an indicator for the banks' income structure, we use the share of non-interest income in total income as a proxy for the extent to which they engage in non-traditional income-generating activities.[18]

5. Results

In section 5.1 we discuss the results for the euro area; next we examine the results for the sample of U.S. banks. In section 5.3 we analyze the total impact of an expansionary monetary policy shock in both regions in order to assess the economic impact of monetary policy actions on bank stability.

5.1 Euro Area

In table 3 we report the impact of an expansionary monetary policy shock on banks' systemic risk exposure based on the specification in equation (6). As outlined in section 3.3, we consider the effect on the change of the stressed market value (ΔSMV) as well as on its two components. The change of the market value (ΔMV) and the change of the $LRMES$ ($\Delta LRMES$) reflect the shift in the stock market's assessment of the banks' value and vulnerability to systemwide downward shocks, respectively. Given that the interest of this paper lies in the heterogeneity of banks' responses to monetary policy, we only present the coefficients of the interaction effects (β_0 to β_K in equation (6)). However, to more easily assess the importance of allowing for bank heterogeneity, we also show for each regression an

[18]Because non-interest income has in some cases become negative during the financial crisis, we calculate the share of non-interest income by dividing the absolute value of non-interest income by the sum of the absolute values of non-interest income and net interest income (see, e.g., Köhler 2015 and Mergaerts and Vander Vennet 2016 for similar approaches).

Table 3. Baseline Regression Results

	Euro Area						United States					
	ΔLong-Run MES		ΔMarket Value		ΔStressed *MV*		ΔLong-Run MES		ΔMarket Value		ΔStressed *MV*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	0.003	0.019*	0.020***	−0.011	0.012**	−0.099*	0.028***	−0.091***	0.017	−0.009	−0.036	0.197**
	(0.003)	(0.011)	(0.002)	(0.012)	(0.005)	(0.053)	(0.009)	(0.033)	(0.012)	(0.038)	(0.022)	(0.082)
Loans to		−0.004		−0.015***		−0.018		0.021		0.012		−0.031
Assets		(0.005)		(0.005)		(0.021)		(0.021)		(0.021)		(0.041)
NPL to		−0.013		−0.019		0.026		−0.049		−0.052		−0.087
Loans		(0.019)		(0.030)		(0.049)		(0.171)		(0.189)		(0.346)
RWA to		−0.010		0.025***		0.041***		−0.055***		0.065*		0.147***
Assets		(0.007)		(0.009)		(0.015)		(0.020)		(0.035)		(0.050)
Size		−0.000		0.002***		0.005**		0.006***		0.004		−0.011*
		(0.000)		(0.001)		(0.002)		(0.002)		(0.003)		(0.006)
Dep. to		−0.002		−0.004		0.022		0.063**		−0.057**		−0.161***
Liabilities		(0.006)		(0.006)		(0.027)		(0.025)		(0.026)		(0.051)
Equity to		0.064		−0.130*		−0.061		0.287***		−0.148		−0.647***
Assets		(0.066)		(0.074)		(0.195)		(0.086)		(0.155)		(0.205)
Share of		−0.006		−0.024***		0.002		0.014		−0.051***		−0.079**
NII		(0.005)		(0.007)		(0.018)		(0.011)		(0.020)		(0.036)
R^2 (within)	0.006	0.008	0.181	0.204	0.018	0.024	0.033	0.042	0.019	0.027	0.013	0.022
Wald (χ^2_7)	–	21.11***	–	54.70***	–	27.96***	–	22.02***	–	10.94	–	16.86**
Obs.	4,502						24,508					
Banks	63						438					

Notes: This table shows only the coefficients of the interaction effects β_i $(i = 0 \ldots K)$ as presented in equation (6). The model is estimated using bank fixed effects. A Wald test is used to test the joint significance of the interaction effects (β_1 to β_K). Standard errors in parentheses are clustered on both the bank and month level to control for within-bank autocorrelation and common shocks. *, **, and *** represent significance at the 10 percent, 5 percent, and 1 percent level, respectively.

intercept-only model and a Wald test for the joint significance of the interaction effects, i.e., β_1 to β_K.

In the "Euro Area" columns of table 3 we present the baseline results for the euro area. With respect to the constant-only regressions, we find that the impact of an expansionary monetary policy shock on *LRMES* and *MV* is mainly positive, implying that for most banks accommodative monetary policy actions increase banks' systemic vulnerability as well as the market value of their equity capital. More specifically, an expansionary unit monetary policy shock is associated with an increase in *LRMES* of 0.3 percentage points and the *MV* of 2 percent. The average change in *SMV* is positive, because the positive impact on the market value dominates, resulting in an average effect of 1.2 percent.

Next, we analyze the heterogeneous impact of monetary policy across bank business models. With respect to asset structure, the results in table 3 show that an expansionary monetary policy shock reduces systemic risk more for banks with higher asset risk. The interaction term of the monetary policy shock with the RWA density is negative for *LRMES* and positive for the market value and stressed market value, although the effect on *LRMES* is not statistically significant. This result is consistent with an expansionary monetary policy shock improving the financial environment, since increasing security prices cause a positive revaluation of the banks' securities portfolios. Moreover, improved collateral values may furthermore decrease the probability of default within the banks' loan portfolios. Our results indicate that the stock market acknowledges these effects, which translates into a beneficial effect of expansionary monetary policy shocks on systemic risk for banks with high asset risk.

Considering the composition of a bank's assets, we find limited evidence for a negative impact of the loan ratio on the transmission of an expansionary monetary policy shock to the market value of euro-area banks: the interaction term of the monetary policy shock and the loan ratio is significantly negative. Based on the discussion in section 2.2, a negative coefficient is consistent with two hypotheses. On the one hand, a high loan ratio could make banks more vulnerable to a long period of near-zero short-term interest rates and decreasing long-term interest rates, provoking a negative revenue effect. However, easing liquidity and financing conditions could also allow banks to defer acknowledging bad loans, i.e., a forbearance channel. The assessment of the relative strength of these hypotheses requires a deeper inspection of the results. First, in table 3 we find that the interaction term of the non-interest income share and the monetary policy shock negatively affects market value. Hence, banks that rely more on net interest revenues appear to benefit from expansionary monetary policy actions. This result is not consistent with monetary policy decreasing bank profitability through the net interest margin, because this hypothesis would suggest that especially banks characterized by a high reliance on net interest income are vulnerable to expansionary shocks.

In order to discriminate between the two hypotheses, we use the regional heterogeneity in the euro area. Doubts about the quality of banks' loan books are likely to be stronger in euro-area periphery countries, since these countries experienced deeper recessions and weaker recoveries. Lower asset quality, combined with higher exposure to distressed sovereign debt, which depresses bank profitability and capital buffers, may increase forbearance incentives for banks in these countries. Such forbearance would, however, negatively affect current profitability and lead to future loan impairments (see Peek and Rosengren 2005). Acharya et al. (2019) find that the OMT program in the euro area allowed banks to evergreen distressed loans and that this effect was especially strong in the peripheral countries. However, if the negative effect of the loan ratio interaction works through a decrease of the net interest margin, one would expect that the impact is negative in both the periphery and the core. The results in table 4 support the forbearance hypothesis: the effect of the loan ratio interaction on MV and SMV is significantly negative for the periphery but not for the core countries.

Going back to table 3, we do not find any statistically significant results with regard to the funding structure. However, concerning the capital structure, we find that the MV of the highly capitalized banks decreases more than that of the lowly capitalized banks. The subsample analysis comparing the core and the periphery euro-area countries presented in table 4 indicates that this effect is only present in the euro-area periphery: the effects on both the market value and stressed market value are significantly negative. Because funding conditions worsened more for banks in periphery countries,

Table 4. Panel Regression Results: Exploiting the Regional Differences within the Euro Area to Examine the Transmission of Monetary Policy Shocks

	Euro Periphery[a]						Euro Core					
	ΔLong-Run MES		**ΔMarket Value**		**ΔStressed *MV***		**ΔLong-Run MES**		**ΔMarket Value**		**ΔStressed *MV***	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Constant	0.002	0.014	0.019***	−0.010	0.017***	−0.033	0.005**	0.035***	0.020***	−0.034	0.003	−0.127*
	(0.003)	(0.011)	(0.003)	(0.017)	(0.006)	(0.032)	(0.002)	(0.012)	(0.003)	(0.021)	(0.007)	(0.072)
Loans to Assets		0.008		−0.021***		−0.038***		−0.012		−0.005		−0.040
		(0.008)		(0.007)		(0.015)		(0.007)		(0.010)		(0.061)
NPL to Loans		−0.014		−0.010		0.011		−0.012		−0.086*		0.077
		(0.019)		(0.038)		(0.051)		(0.044)		(0.046)		(0.151)
RWA to Assets		−0.015		0.024*		0.040**		−0.002		0.035***		−0.023
		(0.009)		(0.013)		(0.019)		(0.011)		(0.010)		(0.052)
Size		−0.001*		0.003***		0.005***		−0.001		0.003***		0.006*
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.003)
Dep. to Liabilities		0.004		−0.006		−0.019		−0.004		−0.010		0.075
		(0.007)		(0.007)		(0.017)		(0.005)		(0.010)		(0.069)
Equity to Assets		0.130*		−0.185**		−0.360**		−0.052		−0.074		0.437
		(0.074)		(0.094)		(0.157)		(0.080)		(0.085)		(0.316)
Share of NII		−0.006		−0.019		−0.006		−0.003		−0.032***		0.003
		(0.010)		(0.012)		(0.028)		(0.006)		(0.009)		(0.028)
R^2 (within)	0.003	0.007	0.167	0.184	0.032	0.042	0.023	0.033	0.274	0.325	0.007	0.033
Wald (χ^2_7)	–	5.84	–	37.29***	–	35.61***	–	56.03***	–	34.63***	–	8.38
Obs.	2,891						1,611					
Banks	37						26					

[a]The periphery countries are Greece, Italy, Ireland, Portugal, and Spain.

Notes: This table shows only the coefficients of the interaction effects $\beta_i (i = 0 \dots K)$ as presented in equation (6). The model is estimated using bank fixed effects. A Wald test is used to test the joint significance of the interaction effects (β_1 to β_K). Standard errors in parentheses are clustered on both the bank and month level to control for within-bank autocorrelation and common shocks. *, **, and *** represent significance at the 10 percent, 5 percent, and 1 percent level, respectively.

while large exposures to distressed sovereign debt put pressure on their capital buffers, it is especially in the periphery countries that a lower capital ratio allows banks to benefit more from expansionary monetary policies.

Finally, results in the "Euro Area" columns of table 3 indicate that bank size, which we include as a control variable, affects the transmission of monetary policy to bank systemic risk. We find that larger banks benefit more from monetary policy shocks in terms of market value and stressed market value. These findings are consistent with Buch, Eickmeier, and Prieto (2014) and Dell'Ariccia, Laeven, and Marquez (2014) who document that, to the extent that size is correlated with market power, larger banks can better protect their net interest margins when an extended period of accommodative monetary policy puts pressure on long-term interest rates.

5.2 United States

The "United States" columns of table 3 present the intercept-only regressions for the United States and indicate that expansionary monetary policy on average increases $LRMES$ by 3 percentage points but that there is no significant impact on the change in MV and SMV. Regarding the heterogeneous impact of monetary policy, we find that most interaction terms are significant and somewhat larger in size compared with the euro-area results. Similar to the euro area, we find that an expansionary monetary policy shock reduces systemic risk more for banks with higher asset risk. This indicates that a recapitalization effect is also present in the transmission of U.S. monetary policy.

Consistent with euro-area results, we find that the interaction term of the non-interest income share and the monetary policy shock negatively affects market value, implying that net interest income benefits from expansionary monetary policy actions. However, we do not find immediate evidence for a forbearance channel, as the loan ratio does not significantly affect the transmission of monetary policy. To further investigate the presence of a forbearance channel, we exploit the higher granularity of the U.S. accounting data in table 5. Forbearance incentives may be larger for banks that rely more on consumer loans or business loans, rather than real estate

Table 5. Panel Regression Results: Exploiting the Granularity of U.S. Data to Examine the Transmission of Monetary Policy Shocks[a]

	ΔLong-Run MES		ΔMarket Value		ΔStressed *MV*	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−0.091***	−0.089*	−0.009	0.013	0.197**	0.204**
	(0.033)	(0.050)	(0.038)	(0.044)	(0.082)	(0.104)
Loans to Earning Assets	0.021		0.012		−0.031	
	(0.021)		(0.021)		(0.041)	
Cons. Loans to Earning Assets		0.020		−0.003		−0.042
		(0.018)		(0.026)		(0.043)
RE Loans to Earning Assets		0.025**		−0.001		−0.045
		(0.012)		(0.019)		(0.030)
Bus. Loans to Earning Assets		0.064***		−0.054*		−0.180***
		(0.017)		(0.028)		(0.039)
Non-Perf. Loans to Loans	−0.049	0.020	−0.052	−0.131	−0.087	−0.285
	(0.171)	(0.179)	(0.189)	(0.190)	(0.346)	(0.354)
RWA to Earning Assets	−0.055***	−0.059***	0.065*	0.067*	0.147***	0.160***
	(0.020)	(0.019)	(0.035)	(0.034)	(0.050)	(0.046)
Size	0.006***	0.007***	0.004	0.002	−0.011*	−0.014**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)	(0.006)
Deposits to Liabilities	0.063**		−0.057**		−0.161***	
	(0.025)		(0.026)		(0.051)	
Share of Core Funding		0.064***		−0.050**		−0.154***
		(0.021)		(0.025)		(0.046)
NSFR		0.014		−0.037*		−0.055
		(0.021)		(0.022)		(0.043)
Equity to Assets	0.287***	0.186***	−0.148	−0.032	−0.647***	−0.378*
	(0.086)	(0.062)	(0.155)	(0.136)	(0.205)	(0.195)
Share of Non-interest Income	0.014		−0.051***		−0.079**	
	(0.011)		(0.020)		(0.036)	
Share of Fee Income		−0.116*		0.254**		0.394***
		(0.066)		(0.115)		(0.137)
Share of Fiduciary Income		−0.027		0.026		0.054
		(0.028)		(0.037)		(0.062)
Share of Trading Income		−0.029		−0.014		0.044
		(0.048)		(0.066)		(0.160)
Share of Insurance Income		0.036		−0.069		−0.130**
		(0.029)		(0.054)		(0.060)
R^2 (within)	0.042	0.046	0.027	0.033	0.022	0.027
Wald	22.02***	41.90***	10.94	31.93***	16.86**	73.17***
Observations	24,508					
Banks	438					

[a]For comparision, we also add the baseline results as presented in table 3.

Notes: This table shows only the coefficients of the interaction effects $\beta_i (i = 0 \ldots K)$ as presented in equation (6). The model is estimated using bank fixed effects. A Wald test is used to test the joint significance of the interaction effects (β_1 to β_K). Standard errors in parentheses are clustered on both the bank and month level to control for within-bank autocorrelation and common shocks. *, **, and *** represent significance at the 10 percent, 5 percent, and 1 percent level, respectively.

loans, because the Federal Reserve explicitly supported the valuation of the latter.[19] Different studies furthermore indicate that these programs indeed had a positive impact on house prices (Gabriel and Lutz 2015; Rahal 2016). However, the results in table 5 are not in line with the forbearance hypothesis. While we do find that a stronger reliance on business loans increases *LRMES* and decreases MV and SMV, we also find that banks that rely more on real estate loans experience a more positive impact on their *LRMES*. The coefficient is, however, smaller than that of the ratio of business loans.

Apart from asset and income structure, the transmission of monetary policy shocks to bank systemic risk may also be influenced by the way a bank funds its activities, i.e., through customer deposits, wholesale debt, or equity capital. Consistent with Mamatzakis and Bermpei (2016), the results in table 3 indicate that a bank's funding structure, captured by the share of deposit funding in total liabilities, significantly affects the transmission of monetary policy to bank systemic risk for U.S. bank holding companies, in contrast to the euro-area banks, where no significant results are found. We find that the interaction term of the deposit ratio and the monetary policy shock has a positive impact on *LRMES* and a significant negative effect on market value. The combination of these effects furthermore translates into a significantly negative effect on the stressed market value. However, these results do not allow us to determine whether these effects are caused by expansionary monetary policy either relieving stock markets' concerns about banks' funding risk or by incentivizing banks with high deposit ratios to take more risk.

To examine this question further, we again turn to the more detailed data for the United States sample in table 5. Applying the weighting scheme of DeYoung and Jang (2016), we construct a variable that mimics the Basel III definition of the net stable funding ratio (*NSFR*) as closely as possible. We furthermore replace the ratio of deposits to liabilities with the ratio of core funding to total funding to better capture the share of insured deposits. The coefficients

[19] In its November 25, 2008 press release the FOMC motivates its decision to purchase mortgage-backed securities by its intention to support property values: "The Federal Reserve ... will initiate a program to purchase the direct obligations of housing-related government-sponsored enterprises. ... This action is being taken to reduce the cost and increase the availability of credit for the purchase of houses, which in turn should support housing markets."

for the share of core funding are in line with the results in table 3. However, we also find suggestive evidence that the *NSFR*, and thus banks' funding risk, negatively affects the impact of monetary policy shocks on market value. As such, these results provide support to both the funding risk hypothesis and the hypothesis that a higher deposit ratio increases agency problems, implying that the failure of depositors to adequately price risk strengthens the risk-taking incentives of banks in response to monetary easing.

In addition, the results in table 3 suggest that the capital structure, measured by the ratio of total equity to total assets, is also relevant for the transmission of monetary policy to systemic risk for U.S. banks. We find a significantly positive impact on *LRMES* and a negative impact on the stressed market value (columns 4 and 6). These results imply that better capitalized banks are perceived by markets to become more systemically risky following an expansionary monetary policy shock, consistent with the existence of a risk-shifting effect (Dell'Ariccia, Laeven, and Suarez 2017) and also in line with the results of Madura and Schnusenberg (2000), Yin and Yang (2013), and Ricci (2015).

Contrary to the euro area, we do not find that larger U.S. banks benefit more in terms of market value, but rather that they become more systemically vulnerable following an expansionary monetary policy shock, which also translates into a negative impact on *SMV*.

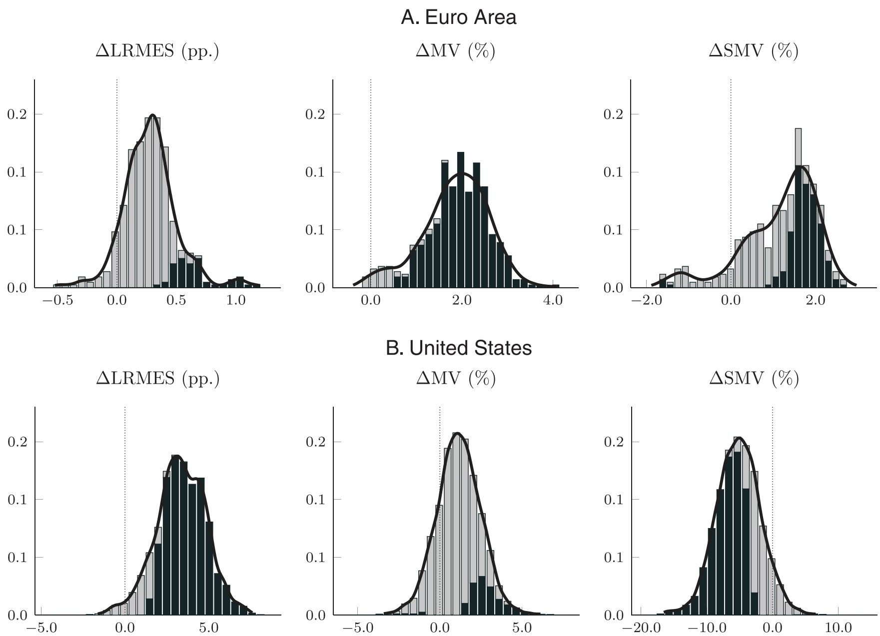
5.3 Total Impact

After analyzing the transmission channels separately, we now discuss the total effect of monetary policy shocks on bank systemic risk in order to assess the economic relevance of monetary policy for bank systemic risk. This enables us to verify which of the transmission channels is dominant in the euro area and the United States. Using the notation of equation (6), we can write the total impact of the monetary policy shock on bank systemic risk in the following way:

$$\frac{\partial Y_{i,t}}{\partial Shock_t} = \hat{\beta}_0 + \sum_{k=1}^{K} \hat{\beta}_k BM_{k,i,t}.$$

In figure 4 we show histograms for both the euro area and the United States of the total impact of monetary policy shocks on each dependent variable, based on the estimation results in table 3. We

Figure 4. Histograms and Estimated Kernel Densities for the Total Impact of a Unit Monetary Policy Shock on Δ*LRMES* (in percentage points), Δ*MV*, and Δ*SMV* (both as percentages) over a One-Month Horizon



Notes: Graphs in this figure are based on the results presented in table 3. The dark parts of the histogram bars represent the proportion of statistically significant (at the 10 percent level) total impacts.

highlight the proportion of impacts that were found to be statistically significant (at the 10 percent level) by using a dark bar, and the proportion that were not found to be significant with a lighter bar. We confirm that the impact of an expansionary monetary policy shock on *LRMES* and *MV* is mainly positive for both the euro area and the United States, implying that for most banks accommodative monetary policy actions increase banks' systemic vulnerability as well as the market value of their equity capital. However, the impact of a monetary policy shock on *LRMES* in the United States tends to be larger than in the euro area. This finding is consistent with the presence of a funding risk channel and risk shifting as the dominating channels operating in the United States. On the contrary, the transmission channels active in the euro area are the forbearance channel and the stealth recapitalization channel. The smaller impact on *LRMES* indicates the dominance of the stealth recapitalization channel which tempers the negative effects of the forbearance channel on bank systemic risk.

We remark that the difference in transmission channels can also be explained by the different sample of banks across both regions. The U.S. banks in our sample are smaller, have a higher capital ratio and lower non-performing loans, and operate in a more traditional business model characterized by a higher loan ratio, more deposit funding, and less reliance on sources of non-interest income than their European counterparts. These banking characteristics are of particular importance in enabling a risk-shifting effect and the funding risk channel.

The results regarding the impact of monetary policy interventions on market value indicate that in the euro area the total impact is statistically significant for most bank-year observations, while this is not the case for the United States. Again, we take this as evidence that the stealth recapitalization channel is more important than and even dominates the forbearance channel for the euro-area banks. For the United States, the total effect of a monetary policy shock on MV is not significant for most observations, indicating that the recapitalization effect is seemingly of lesser importance than the risk-shifting and funding risk effect. Finally, our SMV measure captures the tradeoff between a bank's perceived systemic risk versus its resilience to shocks based on its equity market value. For the euro area the majority of bank-year observations exhibit a positive effect on SMV, because the positive impact on market value dominates through the stealth recapitalization channel. In contrast, for most U.S. bank-year observations the impact on *LRMES* is larger than that on MV, resulting in a significantly negative total impact on SMV because of the funding risk channel and risk-shifting effect.

6. Conclusion and Policy Considerations

In this paper we investigate the impact of monetary policy on bank systemic risk in the euro area and the United States and we disentangle the different transmission channels through which monetary policy can affect financial stability. To do so, we first estimate a monetary policy shock for both monetary regimes using the identification-through-heteroskedasticity approach. In a second stage, we use this monetary policy shock to explore how bank systemic risk is affected across different bank business models.

For the euro area, we find evidence suggesting that expansionary monetary policy actions have given banks more room to delay balance sheet repair. Our results also support the existence of a recapitalization channel both in the euro area and in the United States, indicating that accommodative monetary policy actions increase the value of bank (legacy) assets, leading to a higher net worth of the bank. Considering the total effect of expansionary monetary policy, the results suggest that the stealth recapitalization channel dominates the forbearance channel in the euro area, and in particular in the euro-zone periphery. For the United States, we find evidence for a risk-shifting effect. Moreover, the choice of funding also seems to play a role in the transmission of monetary policy for U.S. banks, since banks that rely on deposit funding experience a larger increase in bank systemic risk. This is in line with the hypothesis that a higher proportion of insured deposits can decrease monitoring incentives and increase agency problems.

In the euro area, expansionary monetary policy has supported the banks in the periphery more than those in the core. In this sense, monetary policy has contributed to an increase in financial stability by decreasing regional asymmetries within the euro zone. This also suggests that the switch from monetary policy accommodation to a tightening stance should be gradual and carefully guided in order to avoid disruptions in monetary policy transmission. Since our results indicate the existence of a forbearance channel, it is recommended that the cleanup of bank balance sheets proceed in a swift manner, so that legacy and forbearance issues can be avoided.

References

Acharya, V. V., T. Eisert, C. Eufinger, and C. Hirsch. 2019. "Whatever It Takes: The Real Effects of Unconventional Monetary Policy." Forthcoming in *Review of Financial Studies*. Available at https://doi.org/10.1093/rfs/hhz005.

Acharya, V. V., R. F. Engle, and D. Pierret. 2014. "Testing Macroprudential Stress Tests: The Risk of Regulatory Risk Weights." *Journal of Monetary Economics* 65 (July): 36–53.

Acharya, V. V., R. F. Engle, and M. Richardson. 2012. "Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks." *American Economic Review* 102 (3): 59–64.

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson. 2010. "Measuring Systemic Risk." Working Paper No. 10-02, Federal Reserve Bank of Cleveland.

Adrian, T., and M. K. Brunnermeier. 2016. "CoVaR." *American Economic Review* 106 (7): 1705–41.

Adrian, T., and N. Liang. 2016. "Monetary Policy, Financial Conditions, and Financial Stability." Staff Report No. 690, Federal Reserve Bank of New York.

Altavilla, C., D. Giannone, and M. Lenza. 2014. "The Financial and Macroeconomic Effects of OMT Announcements." Working Paper No. 1707, European Central Bank.

Altunbas, Y., L. Gambacorta, and D. Marques-Ibanez. 2014. "Does Monetary Policy Affect Bank Risk?" *International Journal of Central Banking* 10 (1): 95–135.

Arai, N. 2017. "The Effects of Monetary Policy Announcements at the Zero Lower Bound." *International Journal of Central Banking* 13 (2): 159–96.

Baumeister, C., and L. Benati. 2013. "Unconventional Monetary Policy and the Great Recession: Estimating the Macroeconomic Effects of a Spread Compression at the Zero Lower Bound." *International Journal of Central Banking* 9 (2): 165–212.

Billio, M., M. Getmansky, A. W. Lo, and L. Pelizzon. 2012. "Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors." *Journal of Financial Economics* 104 (3): 535–59.

Bisias, D., M. Flood, A. W. Lo, and S. Valavanis. 2012. "A Survey of Systemic Risk Analytics." *Annual Review of Financial Economics* 4 (1): 255–96.

Boeckx, J., M. Dossche, and G. Peersman. 2017. "Effectiveness and Transmission of the ECB's Balance Sheet Policies." *International Journal of Central Banking* 13 (1): 297–333.

Borio, C., L. Gambacorta, and B. Hofmann. 2015. "The Influence of Monetary Policy on Bank Profitability." Working Paper No. 514, Bank for International Settlements.

Brissimis, S. N., and M. D. Delis. 2010. "Bank Heterogeneity and Monetary Policy Transmission." Working Paper No. 1233, European Central Bank.

Brunnermeier, M. K., and Y. Sannikov. 2014. "A Macroeconomic Model with a Financial Sector." *American Economic Review* 104 (2): 379–421.

Buch, C. M., S. Eickmeier, and E. Prieto. 2014. "In Search for Yield? Survey-Based Evidence on Bank Risk Taking." *Journal of Economic Dynamics and Control* 43 (June): 12–30.

Busch, R., and C. Memmel. 2015. "Banks' Net Interest Margin and the Level of Interest Rates." Discussion Paper No. 16/2015, Deutsche Bundesbank.

Cappiello, L., R. F. Engle, and K. Sheppard. 2006. "Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns." *Journal of Financial Econometrics* 4 (4): 537–72.

Chen, Q., A. J. Filardo, D. He, and F. Zhu. 2012. "International Spillovers of Central Bank Balance Sheet Policies." *BIS Papers* 66 (September): 230–74.

———. 2016. "Financial Crisis, US Unconventional Monetary Policy and International Spillovers." *Journal of International Money and Finance* 67 (October): 62–81.

Chodorow-Reich, G. 2014. "Effects of Unconventional Monetary Policy on Financial Institutions." *Brookings Papers on Economic Activity* (Spring): 155–228.

De Nicolò, G., G. Dell'Ariccia, L. Laeven, and F. Valencia. 2010. "Monetary Policy and Bank Risk-Taking." Staff Position Note No. 10/09, International Monetary Fund.

Delis, M. D., and G. P. Kouretas. 2011. "Interest Rates and Bank Risk-taking." *Journal of Banking and Finance* 35 (4): 840–55.

Dell'Ariccia, G., L. Laeven, and R. Marquez. 2014. "Real Interest Rates, Leverage, and Bank Risk-taking." *Journal of Economic Theory* 149 (January): 65–99.

Dell'Ariccia, G., L. Laeven, and G. Suarez. 2017. "Bank Leverage and Monetary Policy's Risk-taking Channel: Evidence from the United States." *Journal of Finance* 72 (2): 613–54.

Demirgüç-Kunt, A., and E. Detragiache. 2002. "Does Deposit Insurance Increase Banking System Stability? An Empirical Investigation." *Journal of Monetary Economics* 49 (7): 1373–1406.

Demirgüç-Kunt, A., and H. Huizinga. 2004. "Market Discipline and Deposit Insurance." *Journal of Monetary Economics* 51 (2): 375–99.

DeYoung, R., and K. Y. Jang. 2016. "Do Banks Actively Manage Their Liquidity?" *Journal of Banking and Finance* 66 (May): 143–61.

Gabriel, S. A., and C. Lutz. 2015. "The Impact of Unconventional Monetary Policy on Real Estate Markets." Mimeo.

Gagnon, J., M. Raskin, J. Remache, and B. P. Sack. 2011. "Large-Scale Asset Purchases by the Federal Reserve: Did They Work?" *Economic Policy Review* (Federal Reserve Bank of New York) 17 (1): 41–59.

Gambacorta, L., B. Hofmann, and G. Peersman. 2014. "The Effectiveness of Unconventional Monetary Policy at the Zero Lower Bound: A Cross-Country Analysis." *Journal of Money, Credit and Banking* 46 (4): 615–42.

Gambacorta, L., and H. S. Shin. 2018. "Why Bank Capital Matters for Monetary Policy." *Journal of Financial Intermediation* 35 (Part B): 17–29.

Garcia Pascual, A., and T. Wieladek. 2016. "The European Central Bank's QE: A New Hope." CESifo Working Paper No. 5946.

Garrido, J., E. Kopp, and A. Weber. 2016. "Cleaning-up Bank Balance Sheets: Economic, Legal, and Supervisory Measures for Italy." Working Paper No. 16/135, International Monetary Fund.

Gilchrist, S., D. Lopez-Salido, and E. Zakrajsek. 2015. "Monetary Policy and Real Borrowing Costs at the Zero Lower Bound." *American Economic Journal: Macroeconomics* 7 (1): 77–109.

Gilchrist, S., and E. Zakrajsek. 2013. "The Impact of the Federal Reserve's Large-Scale Asset Purchase Programs on Corporate Credit Risk." *Journal of Money, Credit and Banking* 45 (s2): 29–57.

Huang, X., H. Zhou, and H. Zhu. 2012. "Systemic Risk Contributions." *Journal of Financial Services Research* 42 (1–2): 55–83.

Ioannidou, V., S. Ongena, and J. L. Peydró. 2015. "Monetary Policy, Risk-taking, and Pricing: Evidence from a Quasi-natural Experiment." *Review of Finance* 19 (1): 95–144.

Jiménez, G., S. Ongena, J. L. Peydró, and J. Saurina. 2014. "Hazardous Times for Monetary Policy: What Do Twenty Three Million Bank Loans Say about the Effects of Monetary Policy on Credit Risk Taking?" *Econometrica* 82 (2): 463–505.

Joyce, M., A. Lasaosa, I. Stevens, and M. Tong. 2011. "The Financial Market Impact of Quantitative Easing in the United Kingdom." *International Journal of Central Banking* 7 (3): 113–61.

Joyce, M., and M. Tong. 2012. "QE and the Gilt Market: A Disaggregated Analysis." *Economic Journal* 122 (564): 348–84.

Köhler, M. 2015. "Which Banks Are More Risky? The Impact of Business Models on Bank Stability." *Journal of Financial Stability* 16 (February): 195–212.

Krishnamurthy, A., and A. Vissing-Jorgensen. 2011. "The Effects of Quantitative Easing on Interest Rates: Channels and Implications for Policy." *Brookings Papers on Economic Activity* 2 (Fall): 215–87.

Lambert, F., and K. Ueda. 2014. "The Effects of Unconventional Monetary Policies on Bank Soundness." Working Paper No. 14/152, International Monetary Fund.

Lanne, M., and H. Lütkepohl. 2008. "Identifying Monetary Policy Shocks via Changes in Volatility." *Journal of Money, Credit and Banking* 40 (6): 1131–49.

Lombardi, M. J., and F. Zhu. 2014. "A Shadow Policy Rate to Calibrate US Monetary Policy at the Zero Lower Bound." Working Paper No. 452, Bank for International Settlements.

Maddaloni, A., and J. L. Peydró. 2013. "Monetary Policy, Macroprudential Policy, and Banking Stability: Evidence from the Euro Area." *International Journal of Central Banking* 9 (1): 121–69.

Madura, J., and O. Schnusenberg. 2000. "Effect of Federal Reserve Policies on Bank Equity Returns." *Journal of Financial Research* 23 (4): 421–47.

Mamatzakis, E., and T. Bermpei. 2016. "What Is the Effect of Unconventional Monetary Policy on Bank Performance?" *Journal of International Money and Finance* 67 (October): 239–63.

Meaning, J., and F. Zhu. 2011. "The Impact of Recent Central Bank Asset Purchase Programmes." *BIS Quarterly Review* (4, December): 73–83.

Meinusch, A., and P. Tillmann. 2016. "The Macroeconomic Impact of Unconventional Monetary Policy Shocks." *Journal of Macroeconomics* 47 (Part A): 58–67.

Mergaerts, F., and R. Vander Vennet. 2016. "Business Models and Bank Performance: A Long-Term Perspective." *Journal of Financial Stability* 22 (February): 57–75.

Neely, C. J. 2015. "Unconventional Monetary Policy Had Large International Effects." *Journal of Banking and Finance* 52 (March): 101–11.

Paligorova, T., and J. A. C. Santos. 2012. "When Is It Less Costly for Risky Firms to Borrow? Evidence from the Bank Risk-Taking Channel of Monetary Policy." Staff Working Paper No. 2012-10, Bank of Canada.

Peek, J., and E. S. Rosengren. 2005. "Unnatural Selection: Perverse Incentives and the Misallocation of Credit in Japan." *American Economic Review* 95 (4): 1144–66.

Rahal, C. 2016. "Housing Markets and Unconventional Monetary Policy." *Journal of Housing Economics* 32 (June): 67–80.

Rajan, R. G. 2005. "Has Financial Development Made the World Riskier?" In *The Greenspan Era: Lessons for the Future*. Proceedings of the 2005 Economic Symposium sponsored by the Federal Reserve Bank of Kansas City, held in Jackson Hole, Wyoming, August 25–27.

Ricci, O. 2015. "The Impact of Monetary Policy Announcements on the Stock Price of Large European Banks during the Financial Crisis." *Journal of Banking and Finance* 52 (March): 245–55.

Rigobon, R., and B. Sack. 2003. "Measuring the Reaction of Monetary Policy to the Stock Market." *Quarterly Journal of Economics* 118 (2): 639–69.

———. 2004. "The Impact of Monetary Policy on Asset Prices." *Journal of Monetary Economics* 51 (8): 1553–75.

Rogers, J. H., C. Scotti, and J. H. Wright. 2014. "Evaluating Asset-Market Effects of Unconventional Monetary Policy: A Multi-country Review." *Economic Policy* 29 (80): 749–99.

Smets, F. 2014. "Financial Stability and Monetary Policy: How Closely Interlinked?" *International Journal of Central Banking* 10 (2): 263–300.

Swanson, E. T. 2011. "Let's Twist Again: A High-Frequency Event-Study Analysis of Operation Twist and Its Implications for

QE2.” *Brookings Papers on Economic Activity* 42 (1, Spring): 151–207.

Taylor, J. B., and J. C. Williams. 2009. “A Black Swan in the Money Market.” *American Economic Journal: Macroeconomics* 1 (1): 58–83.

van Oordt, M., and C. Zhou. 2014. “Systemic Risk and Bank Business Models.” Working Paper No. 442, De Nederlandsche Bank.

Wright, J. H. 2012. “What Does Monetary Policy Do to Long-term Interest Rates at the Zero Lower Bound?” *Economic Journal* 122 (564): 447–66.

Yin, H., and J. Yang. 2013. “Bank Characteristics and Stock Reactions to Federal Funds Rate Target Changes.” *Applied Financial Economics* 23 (23): 1755–64.

Asset Price Spillovers from Unconventional Monetary Policy: A Global Empirical Perspective*

Domenico Lombardi,[a] Pierre L. Siklos,[a,b] and Samantha St. Amand[a]
[a]Center for International Governance Innovation
[b]Wilfrid Laurier University

This paper sheds new light on spillovers from U.S. monetary policies before, during, and after the 2008–09 global financial crisis by examining the behavior of select financial asset returns and incorporating indicators of the content of U.S. Federal Open Market Committee announcements. The impact of U.S. monetary policies is examined for systemically important and small open advanced economies. U.S. monetary policy surprise easings are found to have decreased yields in advanced economies post-crisis. The impact of the content of U.S. Federal Open Market Committee statements, coded using text analysis software, is also found to be significant but sensitive to the state of the economy.

JEL Codes: G12, G28, E52, E58.

*This is a CIGI-sponsored research project. The opinions in the paper are those of the authors and not the institutions that supported this research. Domenico Lombardi was Director of the Global Economy program at CIGI when this paper was written and revised. Pierre Siklos is a Professor of Economics at Wilfrid Laurier University, the Balsillie School of International Affairs and a CIGI Senior Fellow. Samantha St. Amand was a CIGI Senior Research Associate when the paper was completed. Comments on earlier drafts by the editor, three anonymous referees, and Philip Lane are gratefully acknowledged. Siklos is grateful to the BIS and the Hoover Institution at Stanford University where parts of this paper were written and to CIGI for financing and supporting this research. Previous versions of this paper were presented at the University of Tasmania, the Australian National University, the Canadian Economics Association Conference, an invited session at the 9th International Conference on Computational and Financial Econometrics, and the European Central Bank. A separate online appendix with additional results and estimation details is available at http://www.ijcb.org.

1. Introduction

The notion that monetary policy decisions by central banks can have international spillover effects is not new. In an integrated global financial system, the monetary policy stance of systemically important central banks will have global implications. Analyzing these spillover effects is important: not only are they likely to influence the success of domestic and international macroeconomic policies, but they also affect the likelihood of future international policy cooperation. This topic has taken on even greater urgency since the 2008–09 global financial crisis (GFC) prompted monetary authorities, especially in advanced economies (AEs), to intervene in financial markets on a scale previously unseen. Indeed, the introduction of unconventional monetary policies (UMPs) in some AEs is seen as a potential catalyst for policy spillovers.

This paper sheds new light on the impact of monetary policy spillovers by examining the response to global monetary policy surprises on select financial asset prices in AEs. Our principal contribution is to introduce a new critical element in measuring spillover effects by quantifying the impact of the surprise component in the content of certain announcements by central banks (viz., policy rate statements and minutes of policy committee meetings). The U.S. Federal Reserve (Fed) is the principal source of monetary policy surprises (MPS) in our analysis, and the sample considered in this study covers ten AEs. Expanding the coverage of countries under investigation is another contribution of our study. Five economies are considered systemically important advanced economies (SIAEs) while the remaining five countries in our data are small open advanced economies (SOAEs).

Central bank policy rates in AEs have remained low since the onset of the GFC. As a result, monetary authorities have placed even greater emphasis on policy communication (e.g., Blinder et al. 2008; Williams 2013; Yellen 2013). The policy of forward guidance (e.g., Charbonneau and Rennison 2015; Filardo and Hofmann 2014) is another manifestation of a strategy that highlights the importance of written and verbal communication in the conduct of monetary policy.

Financial markets closely monitor various forms of central bank communication and incorporate future interest rate expectations into asset prices. It is well known, however, that the clarity of written communications varies, as does how such announcements are interpreted by financial markets (e.g., Blinder et al. 2008). Indeed, the impact of communications on expectations is not always predictable. Otherwise, central bankers themselves would not devote as much attention as they have in recent years to improving their communication with the public (e.g., Yellen 2013). Communication has taken on even more importance since several central banks introduced UMPs and drove policy rates to historically low levels (e.g., Cœuré 2017). Therefore, it is plausible that the content of central bank communication contains an additional element that is incompletely captured by standard proxies for monetary policy surprises that rely on financial asset price changes alone.

Rather than merely recording, say, the frequency of specifically chosen words that appear in monetary policy communications (e.g., tightening, loosening), it may be more fruitful to evaluate the overall content of central bank documents.[1] After all, central banks are known to choose their words carefully when crafting press releases and policy committee minutes. The content of central bank written communication reflects the monetary authority's views about both the current and anticipated state of the economy and how the stance of monetary policy is being determined. Consequently, whether the content of a document signals positive or negative sentiment or opinion, to give two examples, can be conveyed by a combination of several different words. Our approach to quantifying content in central bank communication is detailed in section 3.

Most studies of monetary policy spillovers (discussed in section 2) focus only on the period when the crisis began or when UMPs were launched. However, if we are to properly evaluate the effects of UMPs on international policy spillovers, it also seems desirable to consider the impact of surprises when monetary policy was more conventional. Therefore, following recent studies like Chen, Griffoli, and Sahay (2014), Gilchrist, Yue, and Zakrajšek (2016), and Rogers,

[1] There is nothing wrong, of course, with measuring the frequency with which certain words or expressions appear in a document. Indeed, some studies adopt this strategy (see below). The challenge, however, is to identify a set that provides a meaningful representation of the content of central bank documents. We return to this question later.

Scotti, and Wright (2014), our sample also includes a period before the GFC.

To preview the results, U.S. monetary policy surprises are found to lower yields in the United States and in other AEs. International spillover effects tend to be larger in the post-crisis period and affect the longer end of the yield curve. This indicates some success in the U.S. Fed's efforts to influence the longer end of the yield curve by implementing UMPs. More importantly, we find that the content of central bank statements affects the yields of several financial assets. The content of U.S. Federal Open Market Committee (FOMC) press statements is found to affect U.S. and international asset prices differently depending on the state of the economy. For example, in the pre-crisis period, optimistic and pessimistic language in FOMC communications is linked to whether the Fed's outlook is positive or negative, respectively. During the crisis, however, a shock via pessimistic language appears to have been transmitted through the risk-pricing channel. The content of FOMC meeting minutes appears to complement the impact of press statements, mainly during the crisis period and for longer-term yields. This is important because the former type of publication is supposed to reflect the diversity of views inside the committee, while the latter is supposed to communicate the FOMC's consensus view.

The remainder of this paper is organized as follows. Section 2 provides a brief literature review. Section 3 outlines the various facets and challenges involved in estimating the impact of verbal and non-verbal announcements of central bank actions on financial markets, and describes the data employed and econometric specifications. Section 4 summarizes our principal findings based on an investigation of ten economies, and section 5 concludes.

2. Literature Review

In what follows, we focus on the literature that relies on high-frequency data (i.e., daily or intradaily). Typically, studies estimate the relationship between changes in asset price returns—such as bonds, credit default swaps, equity prices, or exchange rates—and some indicator or proxy of monetary policy surprises. The simplest relationship is written as

$$\Delta q_t = \alpha + \beta MPS_t + \varepsilon_t, \tag{1}$$

where Δq_t is the daily (or intradaily) change or return on a particular financial asset and MPS_t proxies monetary policy surprises. When global sources of surprises are added, this gives rise to so-called spillover effects. In the pure event-study approach, Δq_t is evaluated at the time of a monetary policy announcement covering an event window of anywhere from a few minutes to a few days.

Given the relative size and significance of the U.S. financial system to the global financial system, U.S. MPS are the source of spillover effects in our study and have understandably attracted the most interest in the literature. Interest in U.S. policy spillovers is further reinforced by the unprecedented loosening of U.S. monetary policy through quantitative easing (QE) from 2008 to 2014.[2]

Several proxies for MPS have been proposed. They include differences between announced and expected monetary policy decisions, measured through surveys of market participants (e.g., Ehrmann and Fratzscher 2003, 2007) or changes in futures prices of monetary policy interest rates (e.g., Kuttner 2001); dummy variables for monetary policy announcements deemed to be surprises or to contain a surprise element based on a review of news articles (e.g., Rosa 2012); statements by central bankers (e.g., Aizenman, Binici, and Hutchison 2016); or by extracting the surprise component from financial market activity (e.g., Gürkaynak, Sack, and Swanson 2005). We adopt this last approach to measuring MPS, as it has been argued to be superior to other measures (Chen, Griffoli, and Sahay 2014).

Traditional methods used to measure MPS, however, may not capture the subtleties inherent in changing central bank communication over time. We therefore create a new set of variables that capture the surprise element of the *content* of central bank communications. This is viewed as complementing standard measures of MPS. The literature on the impact of this dimension of policymaking on financial markets is briefly discussed below.

It is usually assumed that announcements associated with UMPs are intended to reduce asset returns (i.e., $\beta < 0$). The surprise

[2]As international spillovers can be limited in type and severity by capital controls or other forms of financial repression, we restrict our focus to AEs with open capital accounts.

component might be the precise size of the intervention, as when the Fed announced in September 2012 a monthly program to purchase mortgage bonds. Verbal announcements, however, unaccompanied by immediate policy action, can also affect financial markets by boosting confidence; this was clearly observed in financial markets' reaction, for example, to European Central Bank (ECB) President Mario Draghi's July 2012 assertion to do "whatever it takes to preserve the euro."

Rogers, Scotti, and Wright (2014) examine the financial market effects of UMPs implemented by four major central banks (U.S. Fed, Bank of England, ECB, and Bank of Japan) for a variety of asset prices (equities, bonds, and exchange rates). They conclude that spillovers from the United States to the rest of the world are found to be relatively stronger than global spillovers to the United States, while UMPs affect the long end of the yield curve.[3] In contrast, during "normal" times, the short end of the term structure is influenced by monetary policy.

Other studies in this vein include Aït-Sahalia et al. (2012) and Bastidon, Huchet, and Kocoglu (2016). The former study finds that spillover effects intensified as the financial crisis progressed. The latter study focuses on the more recent sovereign debt crisis in the euro zone and concludes that insufficient forward guidance by the ECB blunted the monetary authorities' attempts at subduing stress in financial markets. Gilchrist, Yue, and Zakrajšek (2016)

[3] Their study relies mainly on robust least squares using intradaily data, but they also estimate vector autoregressions at the daily frequency that identifies shocks of interest via heteroskedasticity. The premise of the approach, established by Rigobon and Sack (2003) and since modified in several directions (e.g., Bohl, Siklos, and Werner 2007; Neely 2014; and Wright 2012), is that monetary policy decisions generate more volatility in financial markets around decision days (i.e., when the FOMC meets) as markets try to forecast what the central bank will say or do following the release of their policy statements. Similarly, Rosa (2016) finds that speeches by the Fed's Chair raise asset price volatility beyond what is considered "normal." Van Dijk, Lumsdaine, and van der Wel (2016) dispute this view, arguing that markets "set up" well in advance of FOMC meetings; thus, volatility is relatively lower around meeting days. We also estimated specifications for the United States that identified coefficients via heteroskedasticity using Lewbel's (2012) method (refer to the online appendix) after confirming that asset price volatility is indeed higher around the time of FOMC meetings, but our conclusions are unchanged.

find that the pass-through effects of unconventional and conventional monetary policy are roughly similar. Fratzscher, Lo Duca, and Straub (2018) suggest that international spillovers associated with Fed UMP announcements had comparatively small effects and diminishing returns. The International Monetary Fund (2013) conducted a broad investigation of spillovers of UMPs; they reported that the impact of monetary policy spillovers is magnified by indirect third-party effects. They also conclude that the "surprise" element of such policies exhibits diminishing effects as markets normalize.

Much has been made concerning the importance of measuring MPS using intradaily data to avoid having changes in yields being contaminated by other events. Nevertheless, many of the aforementioned studies do not find large differences between daily and intradaily data. Indeed, the vast majority of estimates of versions of equation (1) rely primarily on results at the daily frequency (e.g., Krishnamurthy, Nagel, and Vissing-Jorgensen 2017; Altavilla, Giannone, and Lenza 2016; and references therein).

Gürkaynak, Sack, and Swanson (2005) find intradaily estimates are "quite comparable" to results that rely on daily data. The only exceptions were the few days when an employment report was released or during a period when the Fed did not release a policy statement following the conclusion of an FOMC meeting.[4] Rogers, Scotti, and Wright (2014, p. 3) also acknowledge that whether MPS are properly identified at the intradaily frequency "may be questionable." More importantly, intradaily data can only provide inference about the immediate impact of an MPS. If we believe that monetary policy shocks can persist for a time, then an analysis at the daily frequency is not only suitable, it may actually be preferable. After all, as Shin (2017) points out, the "market" is not an individual and there is plenty of evidence that the impact of an announcement on asset prices will not be exhausted within a small window of time around a particular event (e.g., D'Amico 2016).

Turning briefly to the burgeoning literature on qualitative assessments of central bank communication, Blinder et al. (2008) is a recent survey which concludes that central bank communication has

[4]Gilchrist, Yue, and Zakrajšek (2016) assume a sixty-minute window "should allow the market a sufficient amount of time to digest the news contained in announcements," but no justification is provided for this choice.

a separate powerful impact on financial markets. It also stresses that additional work is needed to further our understanding of central bank communication on the transmission and effectiveness of monetary policy. More recently, speeches by several central bankers recognize that efforts aimed at improving central bank communication remain a work in progress (e.g., Haldane 2017 and references therein).

The content of central bank communication is typically evaluated by coding documents according to readers' interpretations (e.g., tightening or loosening of policy), constructed from speeches by central bankers (e.g., Ehrmann and Fratzscher 2007; Hayo, Kutan, and Neuenkirch 2015). Alternatively, content is quantified by estimating the frequency with which certain "bags of words" appear in documents (e.g., Meade, Burk, and Josselyn 2015; Steckler and Symington 2016). The use of a dictionary technique to capture the content or "sentiment" of central bank texts, which is also used in the present study, is becoming more prominent in the relevant literature (e.g., Hubert and Labondance 2017).

Despite central banks' efforts to improve the clarity of signals provided in official communications, interpreting the content of central bank announcements remains less straightforward than the signal from regular macroeconomic releases that are numerical in nature. As Andrade and Le Bihan (2013) demonstrate, even professional forecasters suffer from rational inattention and a sticky information set. More recently, Haldane (2017) suggests that the public's understanding of the content of central bank communication, including those who are immediately affected by decisions made by the monetary authority (e.g., firms and financial markets), is woefully inadequate.

Still, incorporating qualitative elements of monetary policy into our analytical toolkit is found to add considerable value to our understanding of the effectiveness of monetary policy and best practice in central banking (e.g., Hansen, McMahon, and Prat 2014; Neuenkirch 2012; Sturm and De Haan 2011). Furthermore, Hubert and Labondance (2017) find that the content of central bank statements does influence financial market expectations beyond the effects of monetary policy decisions and central bank forecasts. To our knowledge, no research has yet incorporated the content of central bank communication in the study of international spillovers of monetary policy.

3. Data and Econometric Specifications

The sample begins in June 2006 in order to include data near the peak of the last tightening cycle by the U.S. Federal Reserve (based on the level of the federal funds rate), and ends in December 2013. The precise starting point of various samples, however, is dictated by data availability across the economies considered. A long enough sample is needed so that pre- and post-crisis periods can be investigated separately. The subsamples considered are pre-crisis (June 1, 2006–September 14, 2008); crisis (September 15, 2008–September 30, 2009); post-crisis (October 1, 2009–December 31, 2013); and the euro-zone crisis (November 1, 2009–September 6, 2012).[5]

The basic hypothesis being investigated is that monetary policy surprises create cross-border spillover effects. Whereas previous research has focused on the effects of conventionally measured MPS, we add the spillover effects from a content analysis of press releases and monetary policy committee minutes. In addition, we are interested in whether the GFC and its aftermath amplified or moderated the impact of surprises in the content of central bank communications. Since the present study considers cross-country evidence, we also differentiate between domestic and global effects (i.e., primarily from the United States) of MPS.

The reactions to monetary policy surprises in countries cover several time zones. This provides a rationale for observing asset price changes over a two-day period (e.g., as in Ehrmann, Fratzscher, and Rigobon 2011).[6] When the U.S. FOMC's press releases and meeting minutes are published at 2:00 p.m. EST, European and Asian markets have closed for the day. This provides one argument for relying on two-day observations.

Three different indicators of asset price changes are employed. The change in the spread between three-month and ten-year

[5]The subsamples were chosen based on chronologies from three sources: the Federal Reserve Bank of St. Louis's timeline, the Federal Reserve Bank of New York's chronology, and a timeline prepared by the ECB. Dates were also cross-checked with available chronologies used in the literature; for example, Fratzscher, Lo Duca, and Straub (2018) and Rogers, Scotti, and Wright (2014).

[6]We are grateful to an anonymous referee for the suggestion. An earlier version of this paper (available on request) generates results using daily data, and our conclusions are broadly similar to the ones reported below.

sovereign bond yields is used to capture changes along the yield curve, while the two-day log return of ten-year sovereign bond yields captures spillovers at the longer end of the yield curve. The two-day log return of overnight index swap (OIS) with a one-year term to maturity captures fluctuations in short-term yields.[7] The sample includes five SIAEs (the euro zone, Japan, the United Kingdom, the United States, and Switzerland, which is included in this category due to the characteristics of its financial markets) and five SOAEs (Australia, Canada, New Zealand, Norway, and Sweden).

The content of central bank press releases that accompany monetary policy decisions is an important addition to the standard specification (i.e., equation (1)) because we seek to capture changes in the stance of monetary policy even when policy rates do not change.[8] The approach developed by Romer and Romer (1989, 2004) inspires our estimation strategy. They rely on the narrative approach to interpret the FOMC's intentions for the federal funds rate.[9]

Press releases and minutes may contain a component that incorporates a given central bank's expectations. We construct our indicators by applying an algorithm to capture different dimensions of a central bank's discussion about economic conditions and the policy stance.[10] There is the potential that an event, such as an economic news release, might affect the content of central bank statements and

[7]In a previous draft we also used the three-month and one-year LIBOR-OIS spread to capture the impact of spillovers on risk premiums. Due to space constraints, it has been removed from the draft. These results are, however, available in the online appendix.

[8]Alternatively, recent literature has estimated shadow policy rates in an attempt to capture what the policy rate would be if UMPs were incorporated (see Wu and Xia 2016 and references therein). As we are interested in estimating the impact of surprises in the content of certain central bank announcements, we do not pursue this line of inquiry.

[9]The authors identify the central bank's view about the economic outlook from other determinants. Hence, their measure is relatively free of the endogeneity problem that plagues conventional measures of monetary policy. Endogeneity arises in part because expectations of future changes in the monetary policy stance are influenced by current forecasts of the economic outlook that serve as the basis for setting the current stance of monetary policy.

[10]As suggestive evidence that our indicators of content of press releases and meeting minutes are not multicollinear with other measurements of MPS, we estimate the unconditional correlation coefficients with the first principal component of yields on U.S. Treasury futures on the date of monetary policy announcements, which range between –0.03 and –0.13.

asset prices on the date of a central bank announcement. To control for the possibility of an omitted-variable bias, we include ten significant macroeconomic news surprises in the United States (see table 1 for more details). That said, there are some challenges with the adopted strategy. One such limitation is that financial market participants often process central bank news through media reports (Hayo and Neuenkirch 2015). In addition, the news media sometimes concentrate their attention on changes in the language of central bank communications to convey change both in the current stance of policy and the economic outlook; the *Wall Street Journal*, for example, publishes a side-by-side comparison of the FOMC press releases after successive meetings to facilitate comparisons of changes in wording over time. However, the precise way that financial markets interpret U.S. FOMC statements, let alone changes in statements over time, is unknown.

To measure content, we apply a dictionary technique. We define lists of key words that aim to capture specific elements of the content of communication, and normalize the frequency with which the words in these dictionaries appear in each press statement and meeting minutes by the total word count of the document. Although central bank texts are intended for a general audience, words are carefully chosen.[11] The language used in press releases contains a combination of financial and everyday language. In the case of the FOMC minutes, likely read by a smaller and more specialized audience, participants in the meeting are aware that the transcript will be made public, and this has been found to influence not only what they say but also the language used (Acosta 2014; Meade and Stasavage 2008). Indeed, observers often look for clues about surprises based on

[11]The care taken in the language is clear from a reading of FOMC transcripts where officials are presented with alternative wording combinations not only depending on the likely future direction of the stance of monetary policy but also in an attempt to reflect the degree of consensus about the message the FOMC wishes to convey. Part B of the so-called Tealbook (previously part of the Bluebook) prepared for FOMC meetings has a section entitled “Monetary Policy Alternatives” that proposes a few alternatives for the language to be used in the FOMC’s press release; this is discussed at length during each meeting. While staff proposals for policy statements date back at least to 1969, attention to detail in the choice of words has risen over time, with a clear boost around the time of the GFC.

Table 1. Description of Variables

Dependent Variable	Description	Source
Overnight Index Swaps (OIS)	One-year maturity; two-day log return. Note: Data not available for Japan; sample for United Kingdom starts in August 2007.	Thomson Reuters Datastream
Sovereign Bond Spread	Ten-year to three-month spread; difference over two days. Note: Sample period for Australia and euro zone begins June 2010 and January 2007, respectively.	Thomson Reuters Datastream (except euro zone)[a]
Long-Term Sovereign Bond Yield	Ten-year maturity; two-day log return.	Thomson Reuters Datastream (except euro zone)[a]
Independent Variable	**Description**	**Source**
U.S. Monetary Policy Surprises	Includes three variables: first difference of first principal component of U.S. Treasury futures (two-year to thirty-year maturity) on the day of (i) U.S. FOMC monetary policy statements, (ii) U.S. Fed UMP announcements (QE and forward guidance), and (iii) U.S. FOMC minutes release.	U.S. Treasury futures: Thomson Reuters Datastream Monetary policy announcement dates: central bank website
Monetary Policy Communication Content	Change in the content of monetary policy press statements.	Central bank websites
Domestic Monetary Policy Announcements	Dummy variable equal to one on the day of monetary policy press statement.	Central bank websites
Surprise U.S. Macroeconomic Announcements	Difference between the observed value and the most recent forecast, normalized over the sample period. Includes ten key U.S. macroeconomic announcements: GDP growth, unemployment, non-farm payroll, jobless claims, retail sales, consumer credit, durable goods orders, manufacturing, housing starts, and existing home sales.	Econoday
U.S. Purdah Period	Dummy variable equal to one on dates where the purdah period is active for the U.S. FOMC.	Central bank website
Lag of Dependent Variable	See dependent variable.	See dependent variable source

[a]Euro-zone bond yield and bond spread data are taken from the ECB, which includes issuers with triple-A ratings and uses the Svensson (1994) model. We also used the first principal component of asset returns of the major euro-zone economies; our results remained unchanged.

how much, or little, dissent there is in FOMC deliberations (Madeira and Madeira 2016).

Our dictionaries combine those constructed by the DICTION 6.0 algorithm (see Hart, Childers, and Lind 2013), which was initially developed to analyze political texts, and Loughran and McDonald (2011), who developed dictionaries to reflect the unique characteristic of language used in financial texts. Although using an algorithm is a more objective measurement of content, additional sets of words were also considered to incorporate language commonly used in central bank communications. As shown by Loughran and McDonald (2016), because the dictionary approach to text analysis can be sensitive to the choice of words in the dictionaries, we removed words that are believed to be ambiguous in the context of central banking; for example, crisis, unemployment, risk, and protection.[12] Although these terms do typically capture negative or positive sentiment, they are used in more general or clinical ways by central banks.[13] For similar reasons, the constructed dictionaries include inflections rather than stemming words. For example, "stabilize" and "stabilizing" are included in the optimism dictionary, but not "stability," as it is used more ambiguously in the context of central bank communication; using its stemmed form ("stabil-") would not achieve this end.

Our approach can therefore be seen as a method that mixes the qualitative with the quantitative. The three dimensions of content in central bank documents that we are interested in are certainty,

[12]Loughran and McDonald (2016) criticize DICTION because its dictionaries are not ideally suited to capture the tone of finance-related documents. However, they fail to acknowledge that DICTION can accommodate dictionaries constructed by the user.

[13]For example, central banks refer to risk (i.e., upside, downside, or balanced) and unemployment trends in most monetary policy statements. But they are described in a more clinical way; therefore, we cannot say with confidence that additional uses of these terms in any given statement means that the committee has become more pessimistic. A similar argument could be made about the word "crisis"; the GFC might be referred to as an event that led to some bad outcomes, but reference to the event might not imply that the central bank is currently more pessimistic. Furthermore, when we are actually in crisis conditions, central bankers tend to refer to economic or financial "turmoil" (which is included in the pessimism dictionary) rather than "crisis." Despite efforts to adjust for ambiguous meaning, these issues clearly highlight a key challenge of using textual analysis: meaning is often expressed by a complex combination of words.

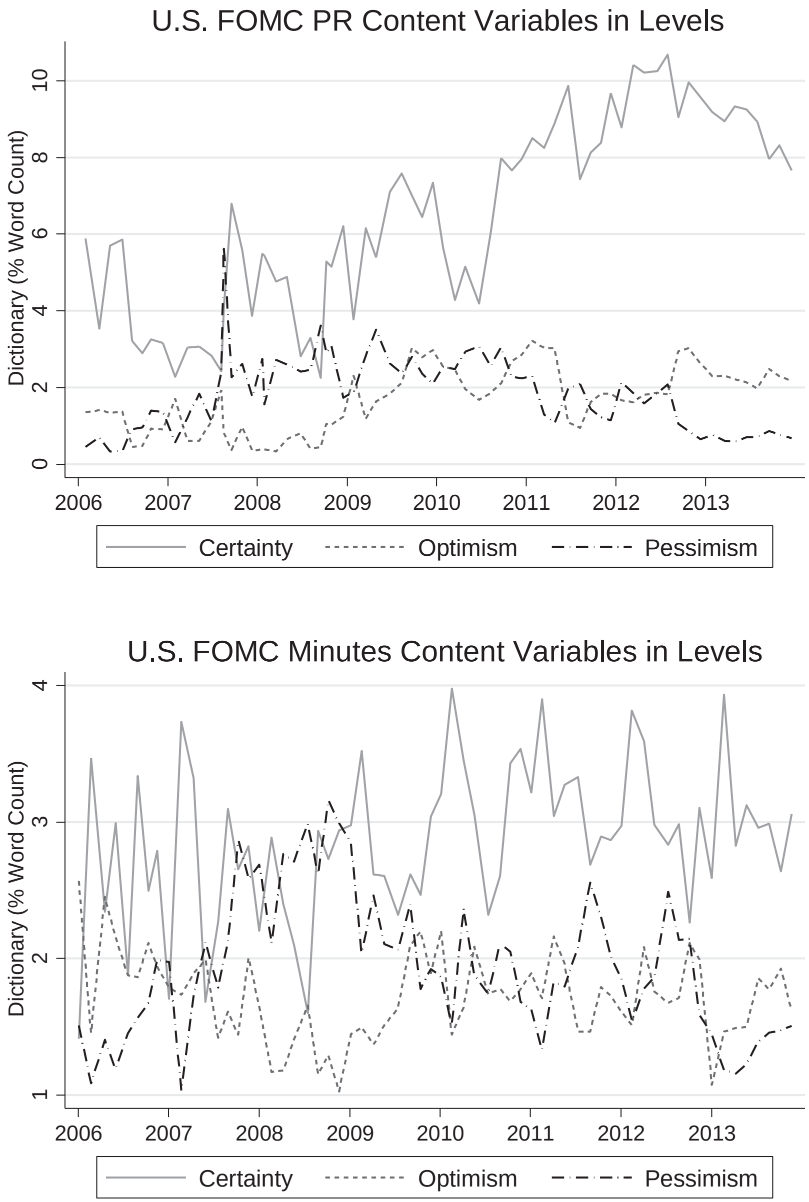
optimism, and pessimism.[14] Briefly, certainty tries to capture the degree to which monetary policy committees make assertions about the state of the economy and the policy stance, and conveys the sense that the committee is speaking with one voice. Earlier research finds that dissent (i.e., a reduction of agreement) inside the FOMC provides important clues about the conduct of U.S. monetary policy (e.g., Thornton and Wheelock 2014). Optimism attempts to capture FOMC language that conveys positive views about the current state of the economy and the contribution made by the current stance of monetary policy. This opens the door to a surprise tightening. In contrast, pessimism attempts to capture sentiment that suggests existing conditions are unsatisfactory. Hence, this raises the possibility of a surprise easing. An online appendix (available at http://www.ijcb.org) provides further details about the composition of these dictionaries.

Figure 1 plots these content variables in levels—the percentage of words that describe content from a dictionary in the total word count of the document—for U.S. FOMC press statements and meeting minutes. The content of central bank communication changes over time, either due to changes in current economic conditions or through deliberate efforts to change the committee's approach to communication, as identified by Meade, Burk, and Josselyn (2015). The graphs illustrate that expressions of certainty, and to a lesser extent optimism, have increased over time in FOMC press releases, while pessimism increased during the crisis and decreased over the post-crisis period. A similar trend is observed in the expression of certainty in FOMC meeting minutes; however, it is less pronounced. Differences in the trends in content of meeting minutes and press releases can be attributed to the fact that press releases are short and deliberately crafted statements, whereas minutes, which are much longer and more detailed, are more descriptive of circumstances.

The surprise element of the content of communication that affects changes in financial asset returns can be measured several ways. The simplest is to take the change in the content variable; therefore, the

[14] In earlier drafts we also considered other indicators of content, but the chosen measures of content likely represent what sentiment financial markets are looking for in central bank press releases and minutes.

Figure 1. U.S. FOMC Content Variables in Levels



Notes: Plotted are the content variables (certainty, optimism, and pessimism) in levels for the U.S. FOMC's press releases (top panel) and meeting minutes (bottom panel). The data represents the percentage of words from each dictionary in the total word count of the document. The sampling frequency is approximately eight times per year on the dates when the FOMC releases its monetary policy statements and meeting minutes. See section 3, and the online appendix provides for further details about the construction of the communications content variables.

surprise content is equal to the change in the percentage of words that convey a certain sentiment (according to a specified dictionary) in the total word count.[15] Other proxies were considered, with little impact on the conclusions.[16]

A rarely discussed consideration in evaluating the empirical evidence about the impact of UMPs is that there are subtle, and not so subtle, differences in both the timing and the coverage of "events" likely to affect asset prices. Some researchers, including Rogers, Scotti, and Wright (2014) who adopt a time-series approach to estimate specifications similar to ours, have resorted to identification through heteroskedasticity (see footnote 3, and Rigobon 2003).[17] We also found differences in the volatility of yield changes and spreads between FOMC meeting days and the remaining days in the sample.[18] We estimate our specifications in the time-series setting using robust least squares (Huber's (1981) M-estimator) to mitigate the impact of outliers that can affect some parameter estimates.

[15]It is worth repeating that observers form expectations about whether the stance of policy will change and not how the wording of press releases, let alone the content of minutes, will change. Whether press releases in successive meetings are written as if the authors start from a blank page is debatable, but even if this is the case, asset return volatility and not their levels will be affected (Ehrmann and Talmi 2016).

[16]There is a possibility that change in the content of statements from meeting to meeting reflects surprises between meetings, rather than a surprise on the day of the meeting. Other studies have found, however, that the central bank statements are themselves a source of new information (e.g., Hubert and Labondance 2017). Furthermore, as we use daily data, these surprises would be priced into asset prices before the date of an announcement. We considered two alternative measures of surprise in the content of central bank statements. The first approach standardizes the percentages over the full sample so that the mean is equal to zero and the standard deviation is equal to one. The second approach takes the deviations from the mean value obtained during the pre-crisis sample. Communications in the pre-crisis period may be taken as a benchmark where less emphasis was placed on the choice of words, as the policy rate was not constrained by the effective lower bound; thus, any deviations from this sample could be taken to be a shock in the content of communications.

[17]The same result cannot be said to hold in all of the other economies in our data set, paralleling the results reported in Rogers, Scotti, and Wright (2014). Identification through heteroskedasticity does not, however, generate different conclusions. See the online appendix for some estimation results.

[18]Summary statistics that support this view are relegated to the online appendix. Also, see footnote 3.

The benchmark specification, an extended version of (1), is written

$$\Delta q_{it} = \alpha_i + \beta \boldsymbol{MPS}_{it} + \theta^j \boldsymbol{\Delta C}^j_{it} + \gamma \boldsymbol{X}^j_{it} + \rho \Delta q_{i(t-1)} + \varepsilon_{it}, \qquad (2)$$

where the subscript i identifies the economy in question while the superscript j identifies whether the determinant of changes in asset prices is domestic or global, where the latter is assumed to originate from the United States. Specification (2) also allows for persistence in asset price changes; Δq represents the two-day log asset return or change in spread, $\boldsymbol{MPS}$ is a vector of monetary policy surprises in the United States, $\boldsymbol{C}$ is a vector of indicators that define the content of the language used by policymakers (as defined above), and $\boldsymbol{X}$ is a vector of additional domestic and global control variables, while Δ is the first-difference operator.[19] U.S. MPS is defined by changes in the first principal component of two-, five-, ten-, and thirty-year U.S. Treasury futures on the date of key monetary policy announcements. Using this methodology, we construct three MPS variables: the first captures the day of U.S. FOMC press releases, the second captures the release of FOMC meeting minutes, and the third captures the dates of U.S. Fed UMP announcements (including QE and forward guidance). Traditionally, the first principal component represents the "level effect" following a MPS, and an increase in MPS represents a surprise loosening of U.S. monetary policy.

In a variant of (2), we allow for the differential impact of tightening versus loosening surprises by interacting $\boldsymbol{C}$ with a Heaviside indicator that identifies episodes where MPS > 0. For this purpose, we use the second principal component of the U.S.-based MPS proxy, as this reflects the impact of monetary policies when short-term interest rates are reduced relative to long-term yields (i.e., a twist of the yield curve; also see Gürkaynak, Sack, and Swanson 2005, and

[19] In estimating (2) and (3) we include dummy variables to capture the announcement of domestic monetary policy decisions, as well as the fact that central banks typically practice purdah—a black-out on central bank news or announcements around days when the monetary policy committee meets (e.g., Ehrmann and Fratzscher 2009). We also include surprise macroeconomic announcements. Refer to table 1 for more details on these measurements. In a previous draft, we added the policy uncertainty measure developed by Baker, Bloom, and Davis (2016) for the United States and other economies where data were available, but this variable proved to be highly insignificant and was dropped.

Rogers, Scotti, and Wright 2014). Normally, a reduction in short-term rates, other things equal, is seen as a loosening of monetary policy. A positive value means that observed yields are lower than expected, which translates into a surprise loosening of policy. The Heaviside variable is labeled $\mathrm{I}(MPS^2 > 0)$, where "2" identifies the second principal component of U.S. MPS. We convert all instances when the policy surprise variable is positive to a dummy variable set equal to unity (and zero otherwise). The specification is thus written

$$\begin{aligned} \Delta q_{it} = \alpha_i + \beta \boldsymbol{MPS}_{it} + \theta^j \boldsymbol{\Delta C}_{it}^j + \theta \boldsymbol{\Delta C}_{it} * \mathrm{I}(MPS^2 > 0) \\ + \gamma \boldsymbol{X}_{it}^j + \rho \Delta q_{i(t-1)} + \varepsilon_{it}, \end{aligned} \tag{3}$$

where $\boldsymbol{MPS}$ and $\boldsymbol{C}$ are as described above, and j includes both domestic and U.S. variants. The purpose of this additional analysis is to verify whether asset prices respond to the surprise content of central bank statements asymmetrically when monetary policy is loosened or tightened. Readers are referred to table 1 for more information on the dependent and independent variables and data sources.

4. Econometric Evidence

Originally, we estimated U.S. spillovers to each economy in the data set. But this generates a considerable number of coefficients, making it challenging to summarize the main findings. Hence, we relegate these estimates to the online appendix. Instead, we present separate estimates for the United States and consider two separate panels consisting of (i) the large and systemically important economies (SIAEs) and (ii) the small-open economies (SOAEs) in the data set.[20] The coefficient estimates of β and θ^{US} from specification (2)—that is, the estimates of the impact of U.S. MPS and content of FOMC documents—are presented in table 2 for the United States and table 3 for a group of SIAEs and SOAEs. Estimates for subsamples are presented in figure 2 to illustrate how the size and influence of spillovers from U.S. MPS have changed over time.

[20] We are grateful to one of the referees for the suggestion. The panel-based results mirror those obtained from pairwise economy estimates.

Table 2. U.S. Regression Estimates

	One-Year OIS	**Bond Spread**	**Ten-Year Yield**
Press Release	−0.01	−0.49***	−0.12***
	(0.05)	(0.10)	(0.03)
UMP Announcement	−0.03	0.13	−0.01
	(0.06)	(0.12)	(0.04)
Minutes Release	0.04	−0.29**	−0.12***
	(0.06)	(0.14)	(0.04)
PR: Certainty	−0.20	−2.36***	−0.2
	(0.47)	(0.89)	(0.28)
PR: Optimism	0.44	−0.71	−0.14
	(1.09)	(2.02)	(0.64)
PR: Pessimism	0.68	2.51*	−0.12
	(0.68)	(1.29)	(0.41)
Minutes: Certainty	−0.47	1.21	0.46
	(0.91)	(2.21)	(0.71)
Minutes: Optimism	0.90	6.4	1.05
	(1.77)	(4.24)	(1.36)
Minutes: Pessimism	0.53	1.57	1.15
	(1.67)	(3.64)	(1.16)
N	1,572	1,335	1,338
R^2 Adjusted	0.29	0.36	0.29

Notes: Estimates for model (2) using robust least squares with standard errors in parentheses. Only the coefficient estimates on the domestic monetary policy surprise (MPS) and U.S. FOMC communications content (C) are reported; the full results are available in the online appendix. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent level, respectively.

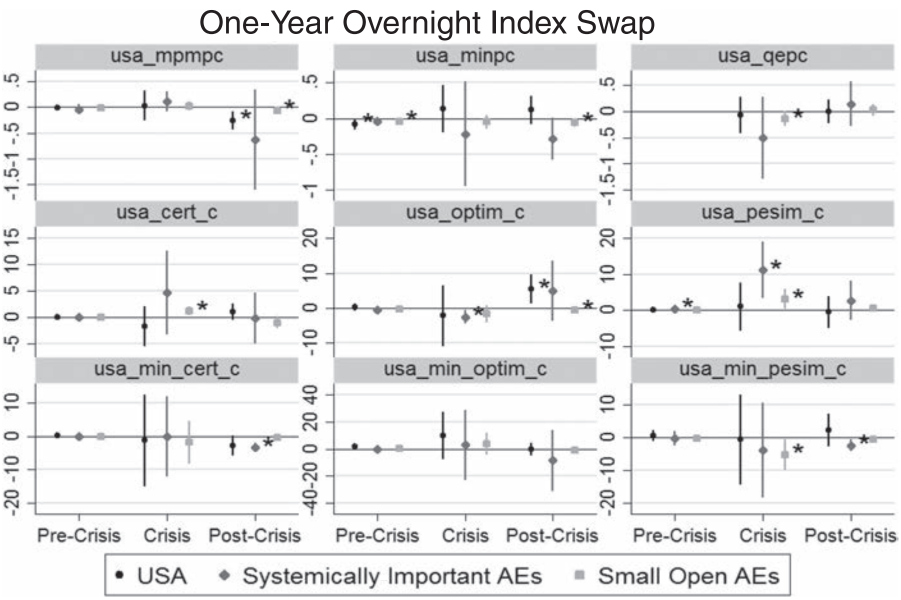
The results suggest that the impact of a positive MPS, that is a surprise easing of U.S. monetary policy, typically reduces yields in both the United States and other AEs. International spillovers appear to be larger in the post-crisis period, and they tend to have a more persistent impact on longer-term sovereign bond yields, consistent with the findings of Rogers, Scotti, and Wright (2014). While the impact of U.S. policies is sometimes relatively greater in magnitude for short-term money markets, this result is found less consistently across sample periods and groups of countries. Unsurprisingly,

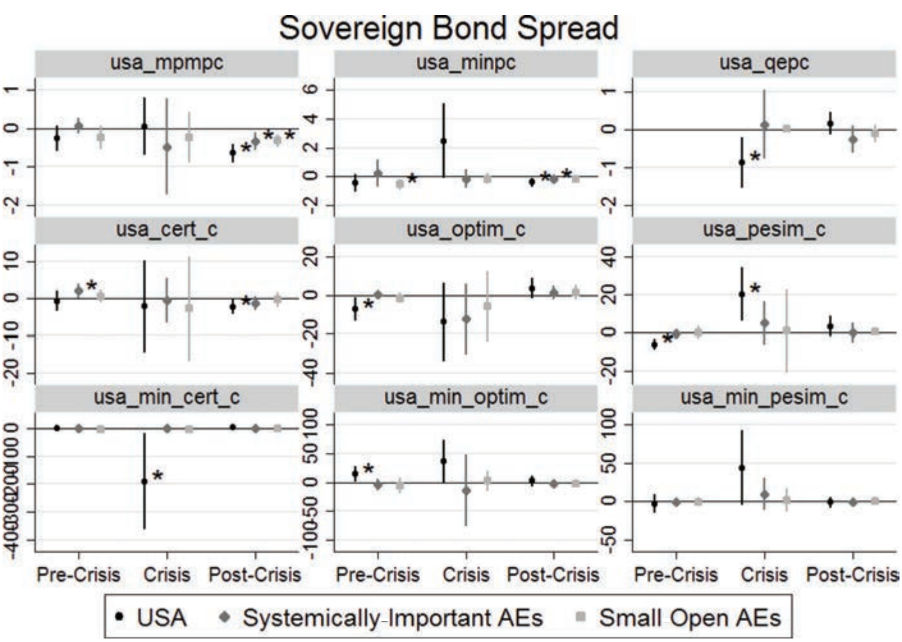
Table 3. Panel Regression Estimates of Spillovers

	One-Year OIS	Bond Spread	Ten-Year Yield
A. Group 1: Systemically Important Advanced Economies (SIAEs)			
Press Release	−0.15	−0.13	−0.06***
	(0.08)	(0.13)	(0.01)
UMP Announcement	−0.07	−0.09	−0.04***
	(0.06)	(0.09)	(0.01)
Minutes Release	−0.22	−0.12	−0.06*
	(0.11)	(0.17)	(0.02)
PR: Certainty	0.56	0.29	0.14**
	(1.01)	(0.50)	(0.04)
PR: Optimism	−0.49	−1.75	−0.49**
	(1.34)	(1.00)	(0.14)
PR: Pessimism	0.80*	−0.41	−0.29*
	(0.22)	(0.25)	(0.09)
Minutes: Certainty	−1.58	−1.06	−0.57
	(1.02)	(1.32)	(0.43)
Minutes: Optimism	−4.96	−3.87	−1.27*
	(3.30)	(3.66)	(0.49)
Minutes: Pessimism	−2.21	1.32	−0.25
	(1.60)	(2.03)	(0.46)
N	3,942	5,460	6,036
R^2 Adjusted	0.13	0.12	0.26
B. Group 2: Small Open Advanced Economies (SOAEs)			
Press Release	−0.01	−0.19	−0.06***
	(0.01)	(0.10)	(0.01)
UMP Announcement	−0.02	−0.03	−0.04*
	(0.03)	(0.06)	(0.02)
Minutes Release	−0.06	−0.26***	−0.06***
	(0.03)	(0.03)	(0.01)
PR: Certainty	−0.42	−0.11	0.03
	(0.37)	(0.73)	(0.08)
PR: Optimism	−0.91*	−0.29	−0.33**
	(0.37)	(0.53)	(0.10)
PR: Pessimism	0.33	0.44	0.06
	(0.27)	(1.05)	(0.06)
Minutes: Certainty	−0.23	−1.52	−0.16
	(0.12)	(1.39)	(0.18)
Minutes: Optimism	−0.06	−2.67	−0.24
	(0.51)	(1.83)	(0.29)
Minutes: Pessimism	−1.16**	0.20	−0.05
	(0.26)	(0.61)	(0.25)
N	7,515	6,522	7,479
R^2 Adjusted	0.31	0.25	0.32

Notes: Estimates for model (2) fixed effects with clustered standard errors in parentheses. Only the coefficient estimates on the monetary policy surprises in the United States (MPS^{US}) and U.S. FOMC communications content (C^{US}) are reported; the full results are available in the online appendix. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent level, respectively. Group 1 are systematically important advanced economies (includes the euro zone, Japan, Switzerland, and the United Kingdom). Group 2 are small open advanced economies (includes Australia, Canada, New Zealand, Norway, and Sweden).

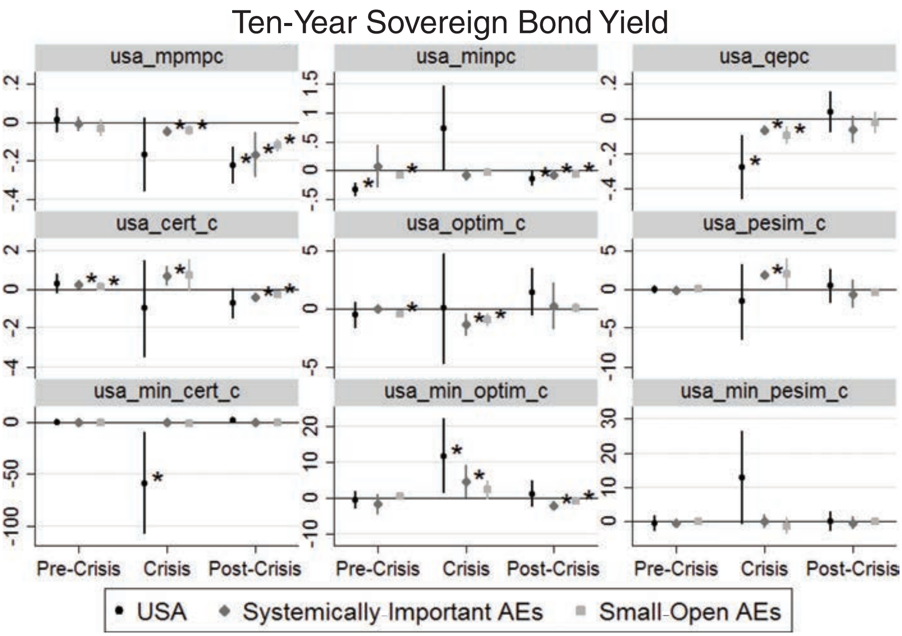
Figure 2. Coefficient Estimates of U.S. Monetary Policy Surprise by Subsample and Group of Countries





(*continued*)

Figure 2. (Continued)



Notes: Plotted are the coefficient estimates and 90 percent confidence intervals for U.S. monetary policy surprises and U.S. FOMC content variables for each dependent variable by sample period. These are the same coefficient estimates that are in tables 2 and 3 (also see section 3), but are estimated over three different sample periods: The pre-crisis period is from June 1, 2006 to September 14, 2008; the crisis period is from September 15, 2008 to September 30, 2009; and the post-crisis period is from October 1, 2009 to December 31, 2013. * indicates that the coefficient estimate immediately to the left is statistically significant at the 10 percent level. *min* refers to the minutes, *mpm* refers to the press releases following a monetary policy meeting, *c* refers to the fact that content is measured, *cert* is certainty, *pes* is pessimism, *optim* is optimism, and *qe* refers to quantitative easing announcements.

U.S. assets are most strongly affected by U.S. MPS. With respect to short-term yields, SOAEs see a decrease in the one-year OIS following a surprise policy easing in the United States. Similar to Chen, Grifolli, and Sahay (2014), we find the impact on longer-term yields appears to be widespread during the post-crisis period, having a statistically significant impact at least at the 95 percent confidence level on assets in both SIAEs and SOAEs, and even after controlling for the content of central bank press releases and minutes. This suggests that the U.S. Fed's efforts to affect the longer end of the yield curve during the crisis and post-crisis periods were not only effective for U.S. assets, but also spread globally. U.S. Fed UMP announcements also appear to be effective in flattening the yield curve and long-term yields in the United States. As with the findings of IMF (2013), UMP announcements had a larger impact during the crisis than in the post-crisis period. Spillover effects from these announcements also lowered long-term yields in other AEs.

The coefficients of the content of U.S. FOMC statements are also included in tables 2 and 3, and in figure 2. Our coefficient plots reveal that the impact of U.S. Fed communications varies across countries and time. Expressions of certainty in U.S. FOMC press releases in the pre-crisis and crisis periods increased long-term yields in both SIAEs and SOAEs. This effect may be related to the idea that sentiment conveying certainty may increase financial market participants' confidence in the economic outlook. During the crisis, expressions of certainty also increased short-term yields in SOAEs; this result could be related to the U.S. Fed's efforts to convey with some immediacy confidence in its ability to address the crisis effectively, which could have resulted in a rise in policy rates in countries that were not as badly affected by the crisis (e.g., Australia, Canada, and New Zealand). In the post-crisis period, however, certainty in press communications tended to reduce long-term yields in other AEs, while it flattened the U.S. yield curve. This appears to reflect a role for global easing from the Fed's bold and sizable QE policies introduced during the crisis and the FOMC's willingness to take more action if necessary. Certainty may also reflect agreement inside the FOMC about maintaining ultra-loose monetary policy for longer than would be expected according to the underlying data or the mechanical application of, say, a Taylor rule.

Turning to the effect of optimism in FOMC press statements, we similarly conclude that its impact varies depending on whether the U.S. economy was in crisis or not. In the pre-crisis period, optimism flattened the yield curve in the United States, perhaps in anticipation of higher short-term yields. During the crisis period, expressions of optimism decreased both short-term and long-term

Table 4. Testing for Statistical Differences

	One-Year OIS		Sovereign Bond Spread		Ten-Year Bond Yield	
Period	**SIAE**	**SOAE**	**SIAE**	**SOAE**	**SIAE**	**SOAE**
Pre-crisis to Crisis	17.29	5.56	1.13	0.01	172.71	4.15
	(0.000)	(0.018)	(0.289)	(0.935)	(0.000)	(0.042)
Crisis to Post-Crisis	3.65	8.30	2.34	0.00	6.39	4.63
	(0.056)	(0.004)	(0.126)	(0.955)	(0.012)	(0.032)

Notes: The table shows the χ^2 statistic and p-value for the Wald test of statistically significant differences in the coefficients between periods. The model is estimated using seemingly unrelated estimation with country fixed effects and clustered standard errors. The pre-crisis period and crisis period, and the crisis and post-crisis period coefficient estimates are compared.

yields in other AEs; this may reflect optimism in the ability of the Fed's policy response to quell the liquidity crisis and reduce financial market volatility. In the post-crisis period, however, optimistic language from the FOMC had a relatively large, positive impact on U.S. short-term yields, and a small, positive effect on SOAE short-term yields; this increase is consistent with the notion that a positive outlook for the U.S. economy could be associated with a tightening of monetary policies.

What stands out most from including a role for the pessimistic content of central bank communication is that the impact is considerably larger during crisis conditions, relative to both the pre-crisis and post-crisis periods at the short end and long end of the yield curve (also see table 4). Pre-crisis, pessimistic content flattened the sovereign bond yield curve in the United States, perhaps reflecting expectations of lower future interest rates. During the crisis period, however, an increase in pessimistic content in FOMC press statements is estimated to increase bond spreads in the United States, which is likely associated with declining short-term yields. Pessimistic sentiment increases short-term and long-term yields in other AEs. This may reflect pessimistic language operating through risk-pricing channels. Risk premiums in both short-term and long-term markets are known to be affected in an environment associated with high uncertainty that characterizes a financial crisis.

Turning briefly to the surprise content of FOMC meeting minutes, the largest impact is clearly observed during the crisis. In this period, an increase in optimism contained in meeting minutes increases long-term sovereign bond yields in the United States and other AEs. This captures the impact of a more favorable outlook for the economy. On the other hand, an increase in expressions of certainty in meeting minutes decreased long-term bond yields in the United States and flattened the yield curve. This provides further evidence that the FOMC's communication of its resolve to maintain an accommodative monetary policy stance—and to consider further easing through UMPs—helped keep long-term bond yield low. Pessimistic content in meeting minutes decreased short-term yields in SOAEs during the crisis, and in SIAEs in the post-crisis period, perhaps a reflection that a weak U.S. economy was associated with a more accommodative policy stance globally. In general, however, it seems that FOMC press releases significantly affect asset prices domestically and internationally regardless of the state of the U.S. economy, while meeting minutes mostly serve as an important additional source of information principally during the crisis period.

Generally, the estimation results suggest the impact of the content of U.S. FOMC statements differs across countries and over time. Results from estimates of equation (3), which permits asymmetric effects, confirm this finding (see the online appendix). Changes in the pessimistic content of central bank statements have a different effect on asset prices when there is a surprise loosening of U.S. Fed monetary policy. Specifically, pessimistic content shocks increase short- and long-term yields, and steepen the yield curve when there is a surprise loosening. Otherwise, the impact is negative. This result indicates that pessimism is associated with heightened uncertainty or risk. The upshot of the foregoing results is that the language of central bank communication acts as an additional variable that significantly affects financial asset prices.

5. Conclusion

Unprecedented actions by central banks in major AEs continue to draw the attention of policymakers and academics. We empirically examine the behavior of financial asset prices in ten economies in response to U.S. monetary policy surprises (MPS). We find that since the GFC, the impact of MPS easings has been to decrease yields in most economies. We also conclude that spillovers from U.S. monetary policy to other systemically important economies as well as small open advanced economies have become larger and more persistent since the end of the GFC. Overall, our empirical results highlight a neglected source of influence on yields before, during, and after the financial crisis: the impact of central bank communication. Our study also provides evidence that central bank communication matters more during periods of financial turmoil and when the policy interest rate is at the zero or effective lower bound. Specific aspects of communication are found to have different effects depending on the state of the economy. However, while the content of FOMC press releases influences yields throughout the entire sample, the minutes appear to exert significant effects on asset prices only during the crisis.

Expressions consistent with certainty significantly reduce long-term yields in the post-crisis period, a reflection of the FOMC's agreement and resoluteness in maintaining accommodative monetary policy since the financial crisis began. Equally important, the spillover effects to the other economies considered, while smaller, are in the same direction. Pre-crisis, greater certainty in central bank content translates into higher long-term yields. We find that during the crisis, short-term yields in the small open economies in our data set rose when FOMC written content was consistent with more certainty about the conduct of monetary policy.

Optimism increases short- and long-term yields in the post-crisis period as financial participants begin anticipating the tightening of the global monetary policy stance. The impact at the short end of the maturity structure is relatively larger. As with the other content variables included in the various estimated specifications, the impact of central bank content is larger for U.S. financial assets than for financial assets elsewhere. Optimism is also found to flatten the yield curve during the crisis, a result that also holds pre-crisis.

Changing pessimism in the content of central bank press releases and minutes also matters, but the impact is relatively larger during the crisis. Spreads during this period are found to increase when there is more pessimism signaled by the Fed, and this sentiment also spills over into the other economies examined here. Indeed, a rise in pessimism is seen as producing a rise in interest rates outside the United States. The bottom line then is that while central bank communication by the Fed can have negative consequences abroad, in the form of higher short-term interest rates, the same communication can also be beneficial because long-term yields decline as the Fed, and the other systemically important central banks, implemented unconventional monetary policies.

There are a number of worthwhile extensions to our analysis that might be contemplated. First, key speeches by central bankers could also be coded using the text software employed in this paper, as this is an additional source of spillovers that is not considered in this study. Second, there may be an element of surprise in the change in the shadow policy interest rate, in addition to the content of press releases. The reason is that prior to the crisis, market participants had become used to discerning the stance of monetary policy via some version of the eponymous Taylor rule. During the crisis, however, some of the central banks in our study reached the effective lower bound (United States, United Kingdom, and the euro zone). Hence, the stance of monetary policy could no longer be easily measured via the observed policy rate. Instead, shadow policy rates have been estimated. We leave these extensions to future research.

References

Acosta, M. 2015. "FOMC Responses to Calls for Transparency." Finance and Economic Discussion Series No. 2015-060, Board of Governors of the Federal Reserve System.

Aizenman, J., M. Binici, and M. M. Hutchison. 2016. "The Transmission of Federal Reserve Tapering News to Emerging Financial Markets." *International Journal of Central Banking* 12 (2, June): 317–56.

Aït-Sahalia, Y., J. Andritzky, A. Jobst, S. Nowak, and N. Tamirisa. 2012. "Market Response to Policy Initiatives during the Global Financial Crisis." *Journal of International Economics* 87 (1): 162–77.

Altavilla, C., D. Giannone, and M. Lenza. 2016. "The Financial and Macroeconomic Effects of the OMT Announcements." *International Journal of Central Banking* 12 (3, September): 29–57.

Andrade, P., and H. Le Bihan. 2013. "Inattentive Professional Forecasters." *Journal of Monetary Economics* 60 (8): 967–82.

Baker, S. R., N. Bloom, and S. J. Davis. 2016. "Measuring Economic Policy Uncertainty." *Quarterly Journal of Economics* 131 (4): 1593–1636.

Bastidon, C., N. Huchet, and Y. Kocoglu. 2016. "Unconventional Monetary Policy in the Eurozone: A Lack of Forward Guidance?" *Emerging Markets Finance and Trade* 52 (1): 76–97.

Blinder, A., M. Ehrmann, M. Fratzscher, J. De Haan, and D.-J. Jansen. 2008. "Central Bank Communication and Monetary Policy: A Survey of Theory and Evidence." NBER Working Paper No. 13932.

Bohl, M., P. L. Siklos, and T. Werner. 2007. "Do Central Banks React to the Stock Market? The Case of the Bundesbank." *Journal of Banking and Finance* 31 (3, March): 719–33.

Charbonneau, K., and L. Rennison. 2015. "Forward Guidance at the Effective Lower Bound: International Experience." Staff Discussion Paper No. 2015-15, Bank of Canada (November).

Chen, J., T. M. Griffoli, and R. Sahay. 2014. "Spillovers from U.S. Monetary Policy on Emerging Markets: Different This Time?" IMF Working Paper No. 14/240 (December).

Cœuré, B. 2017. "Central Bank Communication in a Low Interest Rates Environment." Speech at an event organized by Bruegel, Brussels, March 31.

D'Amico, S. 2016. "Discussion of 'The Financial and Macroeconomic Effects of the OMT Announcements'." *International Journal of Central Banking* 12 (3, September): 56–68.

Draghi, M. 2012. Speech delivered at the Global Investment Conference, London, July 26.

Ehrmann, M., and M. Fratzscher. 2003. "Monetary Policy Announcements and Money Markets: A Transatlantic Perspective." *International Finance* 6 (3): 309–28.

———. 2007. "Communication by Central Bank Committee Members: Different Strategies, Same Effectiveness?" *Journal of Money, Credit and Banking* 39 (2–3): 509–41.

———. 2009. "Purdah—On the Rationale for Central Bank Silence around Policy Meetings." *Journal of Money, Credit and Banking* 41 (2–3): 517–28.

Ehrmann, M., M. Fratzscher, and R. Rigobon. 2011. "Stocks, Bonds, Money Markets and Exchange Rates: Measuring International Financial Transmission." *Journal of Applied Econometrics* 26 (6): 947–74.

Ehrmann, M., and J. Talmi. 2016. "Starting From a Blank Page? Semantic Similarity in Central Bank Communication and Market Volatility." Working Paper No. 2016-37, Bank of Canada (July).

Filardo, A., and B. Hofmann. 2014. "Forward Guidance at the Zero Lower Bound." *BIS Quarterly Review* (March): 37–53.

Fratzscher, M., M. Lo Duca, and R. Straub. 2018. "On the International Spillovers of US Quantitative Easing." *Economic Journal* 128 (608): 330–77.

Gilchrist, S., V. Yue, and E. Zakrajšek. 2016. "The Response of Sovereign Bond Yields to U.S. Monetary Policy." Working Paper (April 22).

Gürkaynak, R. S., B. Sack, and E. T. Swanson. 2005. "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements." *International Journal of Central Banking* 1 (1, May): 55–93.

Haldane, A. 2017. "A Little More Conversation, A Little Less Action." Speech given at the "Macroeconomics and Monetary Policy" Conference, Federal Reserve Bank of San Francisco, March 31.

Hansen, S., M. McMahon, and A. Prat. 2014. "Transparency and Deliberation within the FOMC: A Computational Linguistics Approach." Discussion Paper No. 2014-11, Centre for Macroeconomics.

Hart, R. P., J. P. Childers, and C. J. Lind. 2013. *Political Tone: How Leaders Talk and Why.* Chicago: University of Chicago Press.

Hayo, B., A. Kutan, and M. Neuenkirch. 2015. "Financial Market Reaction to Federal Reserve Communications: Does the Global Financial Crisis Make a Difference?" *Empirica* 42 (1): 185–203.

Hayo, B., and M. Neuenkirch. 2015. "Central Bank Communication in the Financial Crisis: Evidence from a Survey of Financial Market Participants." *Journal of International Money and Finance* 59 (December): 166–81.

Huber, P. J. 1981. *Robust Statistics.* Hoboken, NJ: John Wiley and Sons.

Hubert, P., and F. Labondance. 2017. "Central Bank Sentiment and Policy Expectations." Staff Working Paper No. 648, Bank of England.

International Monetary Fund. 2013. "Unconventional Monetary Policies — Recent Experience and Prospects." IMF Background Paper.

Krishnamurthy, A., S. Nagel, and A. Vissing-Jorgenson. 2017. "ECB Policies Involving Government Bond Purchases: Impacts and Channels." CEPR Discussion Paper No. 12399 (October).

Kuttner, K. N. 2001. "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market." *Journal of Monetary Economics* 47 (3): 523–44.

Lewbel, A. 2012. "Using Heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models." *Journal of Business and Economic Statistics* 30 (1): 67–80.

Loughran, T., and B. McDonald. 2011. "When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks." *Journal of Finance* 66 (1): 35–65.

———. 2016. "Textual Analysis in Accounting and Finance: A Survey." *Journal of Accounting Research* 54 (4, September): 1187–1230.

Madeira, C., and J. Madeira. 2016. "The Effect of FOMC Dissent on Financial Markets." Mimeo (January).

Meade, E. E., M. A. Burk, and J. Josselyn. 2015. "The FOMC Meeting Minutes: An Assessment of Counting Words and the Diversity of Views." FEDS Notes (May 26), Board of Governors of the Federal Reserve System.

Meade, E. E., and D. Stasavage. 2008. "Publicity of Debate and the Incentive to Dissent: Evidence from the US Federal Reserve." *Economic Journal* 118 (528): 695–717.

Neely, C. J. 2014. "How Persistent are Monetary Policy Effects at the Zero Lower Bound?" Working Paper No. 2014-004A, Federal Reserve Bank of St. Louis.

Neuenkirch, M. 2012. "Managing Financial Market Expectations: The Role of Central Bank Transparency and Central Bank Communication." *European Journal of Political Economy* 28 (1): 1–13.

Rigobon, R. 2003. "Identification Through Heteroskedasticity." *Review of Economics and Statistics* 85 (4): 777–92.

Rigobon, R., and B. Sack. 2003. "Measuring the Reaction of Monetary Policy to the Stock Market." *Quarterly Journal of Economics* 118 (2): 639–69.

Rogers, J. H., C. Scotti, and J. H. Wright. 2014. "Evaluating Asset-Market Effects of Unconventional Monetary Policy: A Cross-Country Comparison." International Finance Discussion Paper No. 1101, Board of Governors of the Federal Reserve System.

Romer, C. D., and D. H. Romer. 1989. "Does Monetary Policy Matter? A New Test in the Spirit of Friedman and Schwartz." In *NBER Macroeconomics Annual 1989*, ed. O. J. Blanchard and S. Fischer, 121–84 (chapter 3). Cambridge, MA: The MIT Press.

———. 2004. "A New Measure of Monetary Policy Shocks: Derivation and Implications." *American Economic Review* 94 (4, September): 1055–84.

Rosa, C. 2012. "How 'Unconventional' Are Large-Scale Asset Purchases? The Impact of Monetary Policy on Asset Prices." Staff Report No. 560, Federal Reserve Bank of New York.

———. 2016. "Fedspeak: Who Moves U.S. Asset Prices?" *International Journal of Central Banking* 12 (4, December): 223–61.

Shin, H. S. 2017. "Can Central Banks Talk Too Much?" Speech at the ECB Conference "Communications Challenges for Policy Effectiveness, Accountability, and Reputation," Frankfurt, November 14.

Steckler, H., and H. Symington. 2016. "Evaluating Qualitative Forecasts: The FOMC Minutes." *International Journal of Forecasting* 32 (2): 559–70.

Sturm, J.-E., and J. De Haan. 2011. "Does Central Bank Communication Really Lead to Better Forecasts of Policy Decisions? New Evidence Based on a Taylor Rule Model for the ECB." *Review of World Economics* 147 (1): 41–58.

Svensson, L. E. 1994. "Estimating and Interpreting Forward Interest Rates: Sweden 1992-1994." Discussion Paper No. 1051, Centre for Economic Policy Research.

Thornton, D. L., and D. C. Wheelock. 2014. "Making Sense of Dissents: A History of FOMC Dissents." *Review* (Federal Reserve Bank of St. Louis) 96 (3): 213–28.

van Dijk, D., R. L. Lumsdaine, and M. van der Wel. 2016. "Market Set-up in Advance of Federal Reserve Policy Rate Decisions." *Economic Journal* 126 (592): 618–53.

Williams, J. C. 2013. “Lessons from the Financial Crisis for Unconventional Monetary Policy.” Panel discussion at the NBER Conference, Boston, October 18.

Wright, J. 2012. “What Does Monetary Policy Do to Long-Term Interest Rates at the Zero Lower Bound?” *Economic Journal* 122 (564, November): F447–F466.

Wu, J. C., and F. D. Xia. 2016. “Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound.” *Journal of Money, Credit and Banking* 48 (2–3): 253–91.

Yellen, J. 2013. “Communication in Monetary Policy.” Speech delivered at the Society of American Business Editors and Writers 50th Anniversary Conference, Washington, D.C., April 4.

Online Appendix to Asset Price Spillovers from Unconventional Monetary Policy: A Global Empirical Perspective

Domenico Lombardi,[a] Pierre L. Siklos,[a,b] and
Samantha St. Amand[a]
[a]Center for International Governance Innovation
[b]Wilfrid Laurier University

Appendix A. Monetary Policy Communication Content

The dictionaries used in the algorithm to capture variation in content of central bank communications combine dictionaries constructed by DICTION 6.0 and Loughran and McDonald (2011), and are augmented with words frequently used by central bankers. Each dictionary has a unique set of words. Capitalizations and punctuations are disregarded in the processing of texts. The dictionaries include inflections rather than stemming to be more precise about expressions. For example, “stabilize” and “stabilizing” are included in the optimism dictionary, but not “stability,” as it is used more ambiguously in the context of central bank communication; using its stemmed form “stabil-” would not achieve this end. Words that are ambiguous in the context of central bank communications were removed from the dictionaries (for example, crisis, unemployment, risk, stability, dampen, depress, downward, surprise, protection, and so on).

A1. Certainty

The certainty dictionary combines two dictionaries: one that includes words that capture sentiments of disagreement and uncertainty, which is subtracted from another dictionary that includes words that express agreement and certainty in decisionmaking or expectations.

The agreement/certainty dictionary contains 725 words. It combines three DICTION “bags of words”: leveling term, centrality, and rapport, which express words used to ignore individual differences, denote institutional regularities and/or substantive agreement on core values, and describe attitudinal similarities among groups of people (for example, continuous, reliable, steady, warrant, confirm, majority, normalities). The dictionary was augmented with words frequently used by central banks to express agreement or certainty in decisionmaking or expectations, such as accommodative, anticipate, expect, confident, judge, prepared, and so on.

The uncertainty/disagreement dictionary contains 377 words. It mostly relies on the Loughran and McDonald uncertainty dictionary which includes words like appear, believe, cautious, contingent, might, preliminary, roughly, somewhat, uncertain, and so on. The list was augmented with words such as argue, broadly, careful, disorderly, mixed, monitor, and so on.

A.2 Pessimism

The pessimism dictionary captures words that express unfavorable conditions or bad outcomes. It contains a total of 2,746 words and combines the blame and hardship dictionaries of DICTION with the Loughran and McDonald negative dictionary. Terms include threaten, vulnerable, weak, alarming, unstable, adverse, deteriorate, panic, disruption, distort, fail, hinder, impede, lack, jeopardize, overvalued, setback, stagnate, and so on. The dictionary was augmented with terms like downside, constrain, sharp, slack, soft, tight, and so on.

A.3 Optimism

Opposite to the pessimism dictionary, the optimism dictionary captures words that express favorable conditions or good outcomes. It contains a total of 825 words and combines the praise and satisfaction dictionaries of DICTION with the Loughran and McDonald positive dictionary. Terms include stimulate, satisfy, encourage, enhance, better, boost, desirable, effective, improve, outperform, strengthen, successful, and so on. The dictionary was augmented with terms like balanced, ease, expand, returning, stabilize, support, and well-anchored.

Appendix B. Summary Statistics: Dependent Variables

Table B1 shows the summary statistics for the dependent variables (see table 1 in text) for the United States, systemically important advanced economies (SIAEs), and small open economies (SOAEs) over three samples: full sample period, FOMC non-meeting days, and FOMC meeting days.

Table B1. Summary Statistics: Dependent Variables

		N	Mean	Standard Deviation	Kurtosis
A. One-Year OIS					
Full Sample	US	1,978	−0.38	6.27	11.87
FOMC Non-meeting Days		1,914	−0.33	6.15	12.07
FOMC Meeting Days		64	−1.82	8.99	7.41
Full Sample	SIOA	4,988	−0.26	15.07	109.97
FOMC Non-meeting Days		4,825	−0.23	14.92	112.00
FOMC Meeting Days		163	−1.17	18.99	72.97
Full Sample	SOAE	9,540	−0.11	3.15	27.10
FOMC Non-meeting Days		9.229	−0.09	3.14	27.66
FOMC Meeting Days		311	−0.50	3.28	13.13
B. Sovereign Bond Spread					
Full Sample	US	1,822	0.17	11.67	11.37
FOMC Non-meeting Days		1,759	−0.01	11.16	10.72
FOMC Meeting Days		63	4.97	21.15	5.93
Full Sample	SIOA	7,098	0.09	8.58	17.54
FOMC Non-meeting Days		6,859	0.12	8.52	17.60
FOMC Meeting Days		239	−0.93	10.03	14.99
Full Sample	SOAE	8,425	0.16	9.68	22.99
FOMC Non-meeting Days		8,149	0.12	9.54	23.51
FOMC Meeting Days		276	1.52	13.08	14.08
C. Ten-Year Sovereign Bond Yield					
Full Sample	US	1,824	−0.10	3.17	5.48
FOMC Non-meeting Days		1,761	−0.09	3.09	5.25
FOMC Meeting Days		63	−0.35	4.99	4.44
Full Sample	SIOA	7,704	−0.08	3.01	11.36
FOMC Non-meeting Days		7,449	−0.07	3.00	11.53
FOMC Meeting Days		255	−0.35	3.32	7.91
Full Sample	SOAE	9.597	−0.04	2.29	10.43
FOMC Non-meeting Days		9.283	−0.04	2.28	10.60
FOMC Meeting Days		314	−0.07	2.58	6.84

Appendix C. Daily and Intradaily Data Comparisons: An Illustration

Table C1 shows the log returns of U.S. sovereign bond futures at the two-, five-, and ten-year yield to maturity for FOMC policy announcement days between December 2016 and November 2017. (Datastream and Bloomberg only permit six months to one year of intradaily data downloading; additional historical data would have to be purchased.) The data are calculated for three windows: the full trading day, a wide window (one hour before and two hours after an FOMC press statement), and a narrow window (thirty minutes before and one hour after an FOMC press statement). The yellow highlights statistically significant differences between daily and intradaily yield changes. In June 2017 CPI and retail sales surprises were significant (on the strong side). Both of these announcements are controlled for in the study. In February 2017 the Fed did not raise rates, as originally expected, but did so in March. Our content variables are, for example, designed to pick up these subtleties while the impact of the delay in the federal funds rate increase may well have affected other announcements. All of the important ones are controlled for in our study.

Table C1. Daily and Intradaily Data Comparisons: An Illustration

FOMC Announcement Date	Trading Day	Wide Window	Narrow Window
A. Two-Year Yield			
December 14, 2016	−0.14	−0.17	—
February 1, 2017	—	0.06	0.08
March 15, 2017	0.11	0.14	—
May 2, 2017	0.04	−0.01	0.00
June 14, 2017	0.04	—	−0.05
July 26, 2107	0.09	0.07	0.07
September 20, 2017	−0.06	—	—
November 1, 2017	−0.04	−0.01	−0.04
B. Five-Year Yield			
December 14, 2016	−0.36	−0.66	−0.45
February 1, 2017	−0.07	0.16	0.18
March 15, 2017	0.43	0.39	0.37
May 2, 2017	0.15	0.04	0.03
June 14, 2017	0.20	−0.20	−0.12
July 26, 2017	0.28	0.21	0.21
September 20, 2017	−0.19	—	−0.28
November 1, 2017	−0.05	−0.03	−0.09
C. Ten-Year Yield			
December 14, 2016	−0.41	−0.98	−0.66
February 1, 2017	−0.11	0.18	0.20
March 15, 2017	0.67	0.60	0.60
May 2, 2017	0.19	0.10	0.04
June 14, 2017	0.39	−0.21	−0.21
July 26, 2017	0.35	0.30	0.29
September 20, 2017	0.05	—	—
November 1, 2017	−0.03	−0.06	−0.14

Appendix D. Full Regression Results from Specification (2)

In table D1, estimates for model (2) with standard errors are shown in parentheses. U.S. estimation uses robust least squares; estimation for systemically important advanced economies (SIAEs) and small open advanced economies (SOAEs) use fixed effects with clustered standard errors. U.S. surprise macroeconomic news variables include gross domestic product growth (GDP), existing home sales (EHS), unemployment rate (UNM), non-farm payroll (NFP), retail sales (RTS), housing starts (HGS), consumer credit (CCR), manufacturing index (MFI), jobless claims (JBC), and durable goods orders (DGO). *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table D1. Full Regression Results from Specification (2): United States

	Three-Month LIBOR-OIS Spread	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
FOMC Press Release	−0.02	−0.01	−0.49***	−0.12***
	(0.07)	(0.05)	(0.10)	(0.03)
FOMC UMP Announcement	−0.06	−0.03	0.13	−0.01
	(0.09)	(0.06)	(0.12)	(0.04)
FOMC Minutes Release	0.06	0.04	−0.29**	−0.12***
	(0.10)	(0.06)	(0.14)	(0.04)
U.S. GDP	−0.14	0.46	1.69*	0.63**
	(0.70)	(0.52)	(0.95)	(0.30)
U.S. EHS	−1.04	0.22	1.05	0.43
	(0.68)	(0.51)	(0.93)	(0.30)
U.S. UNM	−1.09	0.39	0.80	0.33
	(0.69)	(0.50)	(0.96)	(0.31)
U.S. NFP	0.65	0.60	1.42	0.76***
	(0.66)	(0.47)	(0.90)	(0.29)
U.S. RTS	0.03	0.98**	2.99***	1.13***
	(0.68)	(0.49)	(0.91)	(0.29)
U.S. HGS	−0.47	0.01	0.30	0.42
	(0.66)	(0.49)	(0.95)	(0.30)
U.S. CCR	−0.11	0.64	0.33	0.29
	(0.70)	(0.50)	(1.03)	(0.33)
U.S. MFI	0.66	0.51	−1.83	0.72*
	(0.89)	(0.56)	(1.16)	(0.37)
U.S. JBC	0.68**	−0.56***	−1.13***	−0.25*
	(0.30)	(0.22)	(0.41)	(1.13)
U.S. DGO	−0.96	−0.06	0.26	−0.30
	(0.70)	(0.49)	(0.95)	(0.30)
FOMC PR: Certainty	0.67	−0.20	−2.36***	−0.20
	(0.62)	(0.47)	(0.89)	(0.28)
FOMC PR: Optimism	0.48	0.44	−0.71	−0.14
	(1.45)	(1.09)	(2.02)	(0.64)
FOMC PR: Pessimism	0.14	0.68	2.51*	−0.12
	(0.91)	(0.68)	(1.29)	(0.41)
FOMC Minutes: Certainty	1.99	−0.47	1.21	0.46
	(1.73)	(0.91)	(2.21)	(0.71)
FOMC Minutes: Optimism	−2.03	0.90	6.40	1.05
	(2.91)	(1.77)	(4.24)	(1.36)
FOMC Minutes: Pessimism	0.28	0.53	1.57	1.15
	(2.72)	(1.67)	(3.64)	(1.16)
U.S. Fed Purdah	−0.50	0.20	0.58	0.10
	(0.35)	(0.25)	(0.48)	(0.15)
Lag Dependent Variable	0.37***	0.41***	0.43***	0.41***
	(0.02)	(0.02)	(0.02)	(0.02)
Constant	−0.07	−0.25**	0.36	−0.06
	(0.17)	(0.12)	(0.24)	(0.08)
N	1,389	1,572	1,335	1,338
R^2-Adjusted	0.29	0.29	0.36	0.29

Table D2. Full Regression Results from Specification (2): SIAEs and SOAEs

	SIAEs				SOAEs			
	Three-Month LIBOR-OIS Spread	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield	Three-Month LIBOR-OIS Spread	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
FOMC Press Release	−0.07	−0.15	−0.13	−0.06***	−0.16**	−0.01	−0.19	−0.06***
	(0.06)	(0.08)	(0.13)	(0.01)	(0.03)	(0.01)	(0.10)	(0.01)
FOMC UMP Announcement	0.19	−0.07	−0.09	−0.04***	0.11	−0.02	−0.03	−0.04*
	(0.11)	(0.06)	(0.09)	(0.01)	(0.07)	(0.03)	(0.06)	(0.02)
FOMC Minutes Release	−0.12	−0.22	−0.12	−0.06*	0.06	−0.06	−0.26***	−0.06***
	(0.06)	(0.11)	(0.17)	(0.02)	(0.06)	(0.03)	(0.03)	(0.01)
U.S. GDP	2.83	1.02	0.15	0.17	0.73*	−0.01	0.55	0.24
	(3.59)	(0.36)	(0.53)	(0.07)	(0.30)	(0.16)	(0.79)	(0.12)
U.S. EHS	0.47	0.92	0.57	0.45***	−1.06	0.17	0.25	0.28*
	(1.04)	(0.40)	(0.62)	(0.07)	(0.53)	(0.11)	(0.71)	(0.12)
U.S. UNM	−0.14	−0.78	−0.74	0.09	1.12	0.23	−0.19	0.15**
	(0.21)	(0.56)	(0.78)	(0.08)	(1.18)	(0.16)	(0.28)	(0.04)
U.S. NFP	1.52	1.29	0.92	0.24	−1.05	0.31	1.10*	0.27*
	(1.13)	(0.95)	(0.55)	(0.13)	(0.91)	(0.18)	(0.48)	(0.11)
U.S. RTS	0.75	0.47	0.69	0.43**	0.82	0.55**	1.72***	0.57***
	(1.06)	(0.18)	(0.30)	(0.10)	(1.32)	(0.18)	(0.17)	(0.08)
U.S. HGS	−0.99	0.10	−0.56*	0.01	0.11	0.23	0.76	0.21
	(0.54)	(0.51)	(0.23)	(0.07)	(0.38)	(0.13)	(0.63)	(0.11)
U.S. CCR	0.90	−0.68**	−1.18	−0.02	−0.49	−0.11	0.14	0.07
	(0.58)	(0.15)	(0.88)	(0.11)	(0.83)	(0.08)	(0.81)	(0.09)
U.S. MFI	2.93	−0.19	0.40	−0.01	−2.01	0.24	0.64	0.15
	(1.69)	(0.84)	(0.74)	(0.33)	(1.05)	(0.17)	(0.39)	(0.08)
U.S. JBC	0.90	−0.11	−0.74	−0.22**	0.31**	−0.17	−0.48**	−0.17***
	(0.57)	(0.15)	(0.33)	(0.06)	(0.08)	(0.14)	(0.14)	(0.03)
U.S. DGO	1.31	0.10	−0.55	−0.16	−1.31*	−0.22*	−0.61	−0.05
	(1.26)	(0.92)	(0.49)	(0.17)	(0.55)	(0.08)	(0.61)	(0.08)
FOMC PR: Certainty	0.12	0.56	0.29	0.14**	0.73	−0.42	−0.11	0.03
	(1.56)	(1.01)	(0.50)	(0.04)	(0.78)	(0.37)	(0.73)	(0.08)
FOMC PR: Optimism	1.90	−0.49	−1.75	−0.49**	4.50*	−0.91*	−0.29	−0.33**
	(2.43)	(1.34)	(1.00)	(0.14)	(1.66)	(0.37)	(0.53)	(0.10)
FOMC PR: Pessimism	2.67	0.80*	−0.41	−0.29*	2.83	0.33	0.44	0.06
	(2.78)	(0.22)	(0.25)	(0.09)	(1.88)	(0.27)	(1.05)	(0.06)

(continued)

Table D2. (Continued)

	SIAEs				SOAEs			
	Three-Month LIBOR-OIS Spread	**One-Year OIS**	**Sovereign Bond Spread**	**Ten-Year Sovereign Bond Yield**	**Three-Month LIBOR-OIS Spread**	**One-Year OIS**	**Sovereign Bond Spread**	**Ten-Year Sovereign Bond Yield**
FOMC Minutes:	3.75	−1.58	−1.06	−0.57	0.57	−0.23	−1.52	−0.16
Certainty	(7.27)	(1.02)	(1.32)	(0.43)	(1.13)	(0.12)	(1.39)	(0.18)
FOMC Minutes:	−2.72	−4.96	−3.87	−1.27*	1.91	−0.06	−2.67	−0.24
Optimism	(8.83)	(3.30)	(3.66)	(0.49)	(2.63)	(0.51)	(1.83)	(0.29)
FOMC Minutes:	5.60	−2.21	1.32	−0.25	0.80	−1.16**	0.20	−0.05
Pessimism	(10.18)	(1.60)	(2.03)	(0.46)	(1.82)	(0.26)	(0.61)	(0.25)
U.S. Fed Purdah	0.22	−1.00*	0.02	0.02	−0.62	−0.03	0.98**	0.19***
	(0.51)	(0.28)	(0.35)	(0.06)	(0.43)	(0.06)	(0.27)	(0.03)
Domestic Monetary	−3.01***	1.03	0.20	0.04	−1.00	−0.08	0.79	0.06
Policy Press Release	(0.34)	(0.88)	(0.33)	(0.04)	(1.03)	(0.24)	(0.48)	(0.13)
Domestic PR:	0.70	0.49	−0.37	0.02	−0.23	−0.12	0.23	−0.03
Certainty	(0.61)	(0.88)	(0.53)	(0.06)	(0.93)	(0.14)	(0.30)	(0.03)
Domestic PR:	−3.12*	2.92	−0.34	0.01	−2.86	−0.21***	−0.55	−0.17
Optimism	(1.09)	(1.16)	(1.59)	(0.13)	(2.11)	(0.03)	(0.46)	(0.18)
Domestic PR:	3.38	−1.59	−0.61	−0.06	2.77*	0.34	−0.77	−0.04
Pessimism	(1.50)	(0.93)	(2.24)	(0.22)	(1.03)	(0.28)	(0.48)	(0.09)
Lag Dependent	0.23**	0.32**	0.34*	0.50***	0.31***	0.53***	0.48***	0.55***
Variable	(0.04)	(0.04)	(0.11)	(0.02)	(0.02)	(0.01)	(0.04)	(0.03)
Constant	0.10	−0.10	0.01	−0.06**	0.29	−0.04***	0.01	−0.05***
	(0.14)	(0.05)	(0.09)	(0.02)	(0.14)	(0.01)	(0.07)	(0.01)
N	4,906	3,942	5,460	6,036	5,122	7,515	6,522	7,479
R^2-Adjusted	0.05	0.13	0.12	0.26	0.10	0.31	0.25	0.32

Appendix E. Regression Results from Specification (2) for Individual Countries

In tables E1–E9, estimates for model (2) using robust least squares with standard errors are shown in parentheses. U.S. surprise macroeconomic news variables include gross domestic product growth (GDP), existing home sales (EHS), unemployment rate (UNM), non-farm payroll (NFP), retail sales (RTS), housing starts (HGS), consumer credit (CCR), manufacturing index (MFI), jobless claims (JBC), and durable goods orders (DGO). U.K. macroeconomic surprises include consumer price index (CPI), gross domestic product growth (GDP), producer price index (PPI), and retail sales (RTS). Euro-area macroeconomic surprises include gross domestic product growth (GDP), harmonized index of consumer prices (HICP), industrial production (IPR), Economic Sentiment Index (ESI) and unemployment rate (UNP). *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table E1. Regression Results from Specification (2): Euro Zone

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
FOMC Press Release	−0.02	−0.18**	−0.04**
	(0.05)	(0.07)	(0.02)
FOMC UMP Announcement	0.02	−0.08	−0.04
	(0.05)	(0.08)	(0.02)
FOMC Minutes Release	−0.06	−0.22**	−0.06**
	(0.05)	(0.09)	(0.02)
U.S. GDP	0.52	0.81	0.30
	(0.46)	(0.70)	(0.19)
U.S. EHS	−0.10	1.44**	0.50***
	(0.45)	(0.66)	(0.19)
U.S. UNM	−0.24	0.21	0.28
	(0.45)	(0.68)	(0.19)
U.S. NFP	0.24	−0.42	−0.04
	(0.42)	(0.65)	(0.18)
U.S. RTS	0.62	0.52	0.28
	(0.43)	(0.69)	(0.18)
U.S. HGS	0.21	−0.10	0.13
	(0.43)	(0.71)	(0.18)
U.S. CCR	0.77*	0.38	0.14
	(0.44)	(0.68)	(0.19)
U.S. MFI	1.13**	0.28	0.14
	(0.51)	(0.83)	(0.23)
U.S. JBC	0.13	−0.32	−0.08
	(0.19)	(0.30)	(0.08)
U.S. DGO	−0.67	0.00	−0.20
	(0.44)	(0.70)	(0.19)
FOMC PR: Certainty	−0.12	1.03	0.12
	(0.41)	(0.69)	(0.17)
FOMC PR: Optimism	−0.94	−0.16	−0.31
	(0.97)	(1.53)	(0.40)
FOMC PR: Pessimism	0.66	−0.31	0.00
	(0.60)	(0.89)	(0.25)
FOMC Minutes: Certainty	−1.07	0.74	−0.07
	(0.83)	(1.43)	(0.35)
FOMC Minutes: Optimism	−3.28**	2.54	−0.09
	(1.57)	(2.63)	(0.72)
FOMC Minutes: Pessimism	−0.95	3.47	0.30
	(1.49)	(2.48)	(0.66)

(*continued*)

Table E1. (Continued)

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
U.S. Fed Purdah	−0.49**	0.46	0.00
	(0.23)	(0.35)	(0.10)
DOM Press Release	−0.17	−0.35	0.01
	(0.43)	(0.65)	(0.18)
DOM UMP Announcements	5.07***	2.32	0.85
	(1.60)	(2.16)	(0.61)
DOM PR: Certainty	−1.79***	0.18	−0.09
	(0.43)	(0.64)	(0.18)
DOM PR: Optimism	2.64***	0.13	0.43*
	(0.61)	(0.93)	(0.25)
DOM PR: Pessimism	−2.33**	−0.69	−0.92**
	(0.96)	(1.44)	(0.40)
DOM GDP	5.12	−0.29	0.35
	(3.71)	(5.46)	(1.53)
DOM HICP	3.34	−1.54	0.39
	(2.61)	(4.36)	(1.10)
DOM IPR	−0.37	−1.57*	−0.37
	(0.61)	(0.90)	(0.25)
DOM ESI	0.23	0.97**	0.32***
	(0.28)	(0.43)	(0.12)
DOM UNM	−4.88	−3.68	−1.52
	(4.27)	(6.55)	(1.81)
DOM Purdah	−0.17	−0.61*	−0.12
	(0.23)	(0.36)	(0.10)
Lag Dependent Variable	0.50***	0.54***	0.54***
	(0.01)	(0.02)	(0.02)
Constant	−0.10	−0.12	−0.03
	(0.13)	(0.20)	(0.05)
N	1,564	1,372	1,488
R^2-Adjusted	0.69	0.34	0.38

Table E2. Regression Results from Specification (2): Japan

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
FOMC Release	—	0.03	−0.04
		(0.04)	(0.03)
FOMC UMP Announcement	—	−0.08	−0.04
		(0.05)	(0.03)
FOMC Minutes Release	—	−0.03	−0.05
		(0.05)	(0.03)
U.S. GDP	—	−0.29	0.00
		(0.44)	(0.28)
U.S. EHS	—	0.86**	0.48*
		(0.43)	(0.28)
U.S. UNM	—	0.22	0.20
		(0.43)	(0.27)
U.S. NFP	—	0.78**	0.65**
		(0.37)	(0.25)
U.S. RTS	—	0.61	0.38
		(0.37)	(0.26)
U.S. HGS	—	−0.25	0.24
		(0.39)	(0.27)
U.S. CCR	—	0.13	0.05
		(0.44)	(0.28)
U.S. MFI	—	0.46	0.10
		(0.44)	(0.30)
U.S. JBC	—	−0.36**	−0.37***
		(0.18)	(0.12)
U.S. DGO	—	0.10	−0.01
		(0.38)	(0.26)
FOMC PR: Certainty	—	−0.05	0.05
		(0.39)	(0.25)
FOMC PR: Optimism	—	−1.03	−0.86
		(0.85)	(0.59)
FOMC PR: Pessimism	—	−1.15**	−0.54
		(0.51)	(0.36)
FOMC Minutes: Certainty	—	−0.48	−0.12
		(0.73)	(0.49)
FOMC Minutes: Optimism	—	−0.83	−1.34
		(1.53)	(0.96)
FOMC Minutes: Pessimism	—	0.17	0.74
		(1.34)	(0.90)

(*continued*)

Table E2. (Continued)

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
U.S. Fed Purdah	—	−0.41*	−0.16
		(0.22)	(0.14)
DOM Press Release	—	0.31	0.41
		(0.47)	(0.30)
DOM Minutes Release	—	−0.31	−0.10
		(0.39)	(0.26)
DOM UMP Announcements	—	1.20	−0.09
		(1.21)	(0.66)
DOM PR: Certainty	—	−0.15	−0.01
		(0.19)	(0.11)
DOM PR: Optimism	—	1.16**	0.38
		(0.49)	(0.29)
DOM PR: Pessimism	—	−0.76*	0.02
		(0.45)	(0.27)
DOM Minutes: Certainty	—	0.46	−0.06
		(0.63)	(0.39)
DOM Minutes: Optimism	—	2.21	0.43
		(1.88)	(1.18)
DOM Minutes: Pessimism	—	−0.70	−0.75
		(1.33)	(0.79)
DOM Purdah	—	−0.41	−0.34*
		(0.30)	(0.19)
Lag Dependent Variable	—	0.50***	0.50***
		(0.02)	(0.02)
Constant	—	0.07	−0.07
		(0.11)	(0.07)
N	—	1,192	1,551
R^2-Adjusted	—	0.27	0.30

Table E3. Regression Results from Specification (2): United Kingdom

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
FOMC Press Release	−0.02	−0.10	−0.05*
	(0.05)	(0.09)	(0.03)
FOMC UMP Announcement	−0.09	−0.24**	−0.16***
	(0.06)	(0.11)	(0.03)
FOMC Minutes Release	−0.06	−0.31**	−0.14***
	(0.06)	(0.12)	(0.04)
U.S. GDP	1.53***	0.89	0.24
	(0.50)	(0.85)	(0.25)
U.S. EHS	0.41	1.27	0.32
	(0.51)	(0.83)	(0.25)
U.S. UNM	−0.16	−0.06	−0.13
	(0.49)	(0.85)	(0.25)
U.S. NFP	0.62	0.55	0.21
	(0.47)	(0.82)	(0.24)
U.S. RTS	−0.54	1.85**	0.59**
	(0.49)	(0.86)	(0.25)
U.S. HGS	−0.32	−1.11	−0.10
	(0.56)	(0.88)	(0.24)
U.S. CCR	0.60	1.78**	0.22
	(0.49)	(0.87)	(0.26)
U.S. MFI	0.72	0.48	0.14
	(0.56)	(1.10)	(0.32)
U.S. JBC	−0.19	−0.43	−0.13
	(0.21)	(0.36)	(0.11)
U.S. DGO	−0.16	−1.23	−0.53**
	(0.53)	(0.86)	(0.26)
FOMC PR: Certainty	−0.47	1.23	0.06
	(0.49)	(0.80)	(0.23)
FOMC PR: Optimism	−2.31*	−1.11	−0.57
	(1.20)	(1.84)	(0.53)
FOMC PR: Pessimism	0.26	−0.72	−0.26
	(0.78)	(1.10)	(0.33)
FOMC Minutes: Certainty	−3.20***	−0.42	−0.06
	(1.21)	(2.12)	(0.61)
FOMC Minutes: Optimism	−2.58	−2.71	−1.14
	(1.97)	(3.54)	(1.05)
FOMC Minutes: Pessimism	−1.97	−2.41	−0.28
	(1.77)	(3.37)	(1.00)

(*continued*)

Table E3. (Continued)

	One-Year OIS	**Sovereign Bond Spread**	**Ten-Year Sovereign Bond Yield**
U.S. Fed Purdah	−0.07	0.03	−0.02
	(0.27)	(0.44)	(0.13)
DOM Press Release	−0.20	0.22	0.11
	(0.53)	(0.87)	(0.25)
DOM Minutes Release	0.27	−0.15	−0.13
	(0.48)	(0.80)	(0.23)
DOM UMP Announcements	0.75	−0.29	0.59
	(1.51)	(2.55)	(0.76)
DOM PR: Certainty	−0.22	−0.37	−0.24
	(0.38)	(0.61)	(0.17)
DOM PR: Optimism	0.62	−5.51***	−0.73
	(1.13)	(1.65)	(0.48)
DOM PR: Pessimism	−1.41*	2.43*	−0.50
	(0.85)	(1.28)	(0.37)
DOM Minutes: Certainty	1.22*	0.35	−0.16
	(0.65)	(1.05)	(0.27)
DOM Minutes: Optimism	1.63	−1.10	−0.98
	(1.47)	(2.43)	(0.72)
DOM Minutes: Pessimism	−2.69*	−2.53	−0.96
	(1.41)	(2.35)	(0.68)
DOM CPI	3.84	0.15	0.20
	(2.59)	(4.29)	(1.26)
DOM GDP	3.54	−2.16	−0.27
	(2.27)	(3.88)	(1.17)
DOM PPI	1.84*	1.21	0.48
	(1.05)	(1.81)	(0.55)
DOM RTS	0.30	0.40	0.22
	(0.51)	(0.88)	(0.26)
DOM Purdah	−0.02	0.05	0.06
	(0.25)	(0.43)	(0.13)
Lag Dependent Variable	0.26***	0.50***	0.50***
	(0.02)	(0.02)	(0.02)
Constant	−0.14	−0.20	−0.14*
	(0.16)	(0.27)	(0.08)
N	1,285	1,316	1,417
R^2-Adjusted	0.17	0.30	0.34

Table E4. Regression Results from Specification (2): Australia

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
FOMC Press Release	−0.02	−0.80***	−0.09***
	(0.02)	(0.14)	(0.02)
FOMC UMP Announcement	0.01	−0.25	−0.04
	(0.02)	(0.16)	(0.02)
FOMC Minutes Release	−0.03	−0.42**	−0.08***
	(0.02)	(0.17)	(0.03)
U.S. GDP	−0.09	0.31	−0.02
	(0.15)	(1.56)	(0.22)
U.S. EHS	0.26*	0.75	0.48**
	(0.15)	(0.89)	(0.20)
U.S. UNM	0.12	−0.61	0.17
	(0.15)	(1.01)	(0.20)
U.S. NFP	0.18	3.64***	0.80***
	(0.14)	(1.26)	(0.19)
U.S. RTS	0.31**	4.10*	0.52**
	(0.14)	(2.26)	(0.21)
U.S. HGS	−0.08	2.53**	0.35*
	(0.15)	(1.20)	(0.19)
U.S. CCR	−0.12	−0.67	0.09
	(0.15)	(1.25)	(0.20)
U.S. MFI	0.15	2.82**	0.39*
	(0.17)	(1.20)	(0.23)
U.S. JBC	0.01	−0.41	−0.19**
	(0.06)	(0.49)	(0.09)
U.S. DGO	−0.10	0.45	0.13
	(0.15)	(1.18)	(0.21)
FOMC PR: Certainty	−0.07	2.66**	−0.03
	(0.14)	(1.20)	(0.19)
FOMC PR: Optimism	0.18	1.13	−0.41
	(0.32)	(3.02)	(0.44)
FOMC PR: Pessimism	−0.03	−2.75	0.01
	(0.20)	(3.49)	(0.27)
FOMC Minutes: Certainty	0.02	−3.30	−0.54
	(0.27)	(2.35)	(0.38)
FOMC Minutes: Optimism	−0.33	−5.65	−0.01
	(0.53)	(4.68)	(0.77)
FOMC Minutes: Pessimism	0.34	−4.24	−0.72
	(0.50)	(4.62)	(0.70)

(*continued*)

Table E4. (Continued)

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
U.S. Fed Purdah	0.11	0.21	0.14
	(0.08)	(0.56)	(0.10)
DOM Press Release	−0.22	1.08	−0.05
	(0.14)	(1.02)	(0.19)
DOM PR: Certainty	−0.10	0.89	0.05
	(0.09)	(0.68)	(0.11)
DOM PR: Optimism	0.05	−0.55	-0.50^{**}
	(0.18)	(1.79)	(0.23)
DOM PR: Pessimism	0.09	-4.66^{***}	0.00
	(0.20)	(1.71)	(0.26)
Lag Dependent Variable	0.47^{***}	0.56^{***}	0.47^{***}
	(0.01)	(0.03)	(0.02)
Constant	−0.05	0.16	−0.01
	(0.04)	(0.26)	(0.05)
N	1,569	656	1,424
R^2-Adjusted	0.42	0.41	0.28

Table E5. Regression Results from Specification (2): Canada

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
FOMC Press Release	0.00	−0.25***	−0.05**
	(0.04)	(0.08)	(0.02)
FOMC UMP Announcement	−0.04	0.03	−0.05*
	(0.04)	(0.10)	(0.03)
FOMC Minutes Release	−0.16***	−0.19	−0.05
	(0.05)	(0.12)	(0.03)
U.S. GDP	0.20	1.64**	0.34
	(0.37)	(0.80)	(0.23)
U.S. EHS	0.49	1.25	0.32
	(0.35)	(0.82)	(0.22)
U.S. UNM	0.39	0.08	0.16
	(0.35)	(0.84)	(0.24)
U.S. NFP	0.46	1.62**	0.37*
	(0.34)	(0.77)	(0.22)
U.S. RTS	0.84**	1.66**	0.55**
	(0.36)	(0.78)	(0.23)
U.S. HGS	0.28	0.87	0.12
	(0.38)	(0.80)	(0.22)
U.S. CCR	0.86**	1.49	0.33
	(0.35)	(0.92)	(0.26)
U.S. MFI	0.20	−0.35	0.31
	(0.41)	(0.98)	(0.28)
U.S. JBC	−0.28*	−0.36	−0.15
	(0.15)	(0.33)	(0.10)
U.S. DGO	−0.11	−1.01	−0.28
	(0.36)	(0.78)	(0.22)
FOMC PR: Certainty	−1.28***	−1.37*	−0.18
	(0.35)	(0.77)	(0.22)
FOMC PR: Optimism	0.22	−1.40	−0.09
	(0.87)	(1.77)	(0.52)
FOMC PR: Pessimism	1.92***	−0.37	−0.19
	(0.60)	(1.06)	(0.31)
FOMC Minutes: Certainty	−0.12	0.48	0.73
	(0.77)	(1.64)	(0.47)
FOMC Minutes: Optimism	0.55	5.34	1.28
	(1.26)	(3.84)	(1.02)
FOMC Minutes: Pessimism	−0.51	3.57	1.28
	(1.21)	(3.34)	(0.95)

(*continued*)

Table E5. (Continued)

	One-Year OIS	**Sovereign Bond Spread**	**Ten-Year Sovereign Bond Yield**
U.S. Fed Purdah	0.01	−0.06	0.18
	(0.19)	(0.43)	(0.12)
DOM Press Release	0.35	1.77*	0.55*
	(0.45)	(1.07)	(0.29)
DOM PR: Certainty	0.03	0.75	0.09
	(0.28)	(0.68)	(0.18)
DOM PR: Optimism	−0.14	0.84	0.14
	(0.51)	(1.08)	(0.29)
DOM PR: Pessimism	−0.08	−0.28	0.06
	(0.65)	(1.59)	(0.39)
DOM Purdah	−0.24	−0.29	−0.05
	(0.23)	(0.54)	(0.15)
Lag Dependent Variable	0.54***	0.42***	0.45***
	(0.02)	(0.02)	(0.02)
Constant	−0.01	0.38	−0.13**
	(0.10)	(0.23)	(0.06)
N	1,386	1,166	1,355
R^2-Adjusted	0.50	0.26	0.29

Table E6. Regression Results from Specification (2): New Zealand

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
FOMC Press Release	−0.01	−0.26***	−0.04***
	(0.01)	(0.07)	(0.01)
FOMC UMP Announcement	0.00	0.05	−0.02
	(0.01)	(0.09)	(0.01)
FOMC Minutes Release	−0.01	−0.14	−0.05***
	(0.01)	(0.09)	(0.01)
U.S. GDP	0.00	2.22***	0.27**
	(0.10)	(0.77)	(0.13)
U.S. EHS	0.02	0.42	0.10
	(0.10)	(0.72)	(0.12)
U.S. UNM	0.07	0.25	0.17
	(0.10)	(0.71)	(0.12)
U.S. NFP	0.05	1.85***	0.15
	(0.10)	(0.66)	(0.11)
U.S. RTS	0.17*	2.05***	0.32***
	(0.10)	(0.68)	(0.12)
U.S. HGS	0.08	0.22	0.28**
	(0.10)	(0.69)	(0.12)
U.S. CCR	−0.21**	−0.55	−0.02
	(0.10)	(0.70)	(0.12)
U.S. MFI	0.07	1.56**	0.17
	(0.11)	(0.79)	(0.13)
U.S. JBC	−0.04	−0.60**	−0.09*
	(0.04)	(0.30)	(0.05)
U.S. DGO	0.08	0.67	0.12
	(0.10)	(0.70)	(0.12)
FOMC PR: Certainty	0.15	−0.19	0.03
	(0.09)	(0.66)	(0.11)
FOMC PR: Optimism	−0.15	0.03	−0.47*
	(0.22)	(1.54)	(0.26)
FOMC PR: Pessimism	−0.02	1.89**	0.01
	(0.14)	(0.96)	(0.16)
FOMC Minutes: Certainty	0.09	−1.08	−0.10
	(0.18)	(1.28)	(0.22)
FOMC Minutes: Optimism	−0.57	−3.81	−0.33
	(0.36)	(2.49)	(0.42)
FOMC Minutes: Pessimism	0.25	3.66	0.38
	(0.34)	(2.35)	(0.40)

(*continued*)

Table E6. (Continued)

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
U.S. Fed Purdah	0.04	0.87**	0.06
	(0.05)	(0.36)	(0.06)
DOM Press Release	−0.11	−0.41	−0.05
	(0.11)	(0.79)	(0.13)
DOM PR: Certainty	0.01	−0.15	−0.05
	(0.05)	(0.36)	(0.06)
DOM PR: Optimism	−0.26**	−0.98	−0.04
	(0.12)	(0.82)	(0.14)
DOM PR: Pessimism	0.19**	−0.51	−0.08
	(0.08)	(0.55)	(0.09)
Lag Dependent Variable	0.43***	0.56***	0.63***
	(0.01)	(0.02)	(0.02)
Constant	0.00	−0.10	−0.03
	(0.02)	(0.17)	(0.03)
N	1,566	1,556	1,556
R^2-Adjusted	0.44	0.49	0.48

Table E7. Regression Results from Specification (2): Norway

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
FOMC Press Release	-0.04^{**}	0.02	-0.02
	(0.01)	(0.08)	(0.02)
FOMC UMP Announcement	-0.04^{**}	-0.11	-0.05^{**}
	(0.02)	(0.10)	(0.02)
FOMC Minutes Release	-0.03^{*}	-0.25^{***}	-0.05^{***}
	(0.02)	(0.10)	(0.02)
U.S. GDP	-0.33^{**}	-0.59	0.06
	(0.14)	(0.83)	(0.17)
U.S. EHS	0.20	0.50	-0.20
	(0.14)	(0.82)	(0.16)
U.S. UNM	-0.03	-0.06	0.01
	(0.14)	(0.80)	(0.16)
U.S. NFP	0.28^{**}	1.12	0.02
	(0.13)	(0.75)	(0.15)
U.S. RTS	0.39^{***}	1.62^{**}	0.34^{**}
	(0.13)	(0.78)	(0.15)
U.S. HGS	0.18	0.15	0.46^{***}
	(0.14)	(0.79)	(0.16)
U.S. CCR	0.00	1.24	0.20
	(0.14)	(0.80)	(0.16)
U.S. MFI	-0.11	0.53	-0.02
	(0.15)	(0.89)	(0.18)
U.S. JBC	-0.03	-0.40	-0.05
	(0.06)	(0.34)	(0.07)
U.S. DGO	0.01	-1.05	-0.13
	(0.14)	(0.79)	(0.16)
FOMC PR: Certainty	-0.13	1.04	0.13
	(0.13)	(0.75)	(0.15)
FOMC PR: Optimism	-0.64^{**}	1.56	-0.38
	(0.30)	(1.76)	(0.35)
FOMC PR: Pessimism	0.19	-1.69	0.25
	(0.19)	(1.09)	(0.22)
FOMC Minutes: Certainty	0.04	1.03	-0.14
	(0.25)	(1.46)	(0.29)
FOMC Minutes: Optimism	0.29	-2.66	-0.56
	(0.49)	(2.83)	(0.56)
FOMC Minutes: Pessimism	0.18	2.98	-0.40
	(0.46)	(2.67)	(0.53)

(*continued*)

Table E7. (Continued)

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
U.S. Fed Purdah	0.01	0.51	0.12
	(0.07)	(0.41)	(0.08)
DOM Press Release	−0.06	0.57	−0.01
	(0.15)	(0.90)	(0.18)
DOM PR: Certainty	−0.23	−0.41	−0.16
	(0.16)	(0.93)	(0.18)
DOM PR: Optimism	−1.12*	5.93	0.57
	(0.65)	(3.78)	(0.75)
DOM PR: Pessimism	−0.05	−1.15	−0.41
	(0.26)	(1.49)	(0.30)
Lag Dependent Variable	0.51***	0.51***	0.58***
	(0.02)	(0.01)	(0.01)
Constant	0.01	−0.56***	−0.10***
	(0.03)	(0.19)	(0.04)
N	1,571	1,572	1,572
R^2-Adjusted	0.42	0.49	0.54

Table E8. Regression Results from Specification (2): Sweden

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
FOMC Press Release	-0.08^{***}	-0.08	-0.06^{***}
	(0.03)	(0.07)	(0.02)
FOMC UMP Announcement	0.09^{***}	-0.22^{**}	-0.15^{***}
	(0.03)	(0.09)	(0.03)
FOMC Minutes Release	-0.05	-0.16^{*}	-0.01
	(0.04)	(0.09)	(0.03)
U.S. GDP	0.25	-0.66	-0.15
	(0.28)	(0.73)	(0.23)
U.S. EHS	0.30	2.32^{***}	0.67^{***}
	(0.27)	(0.71)	(0.23)
U.S. UNM	-0.14	-0.55	0.06
	(0.28)	(0.70)	(0.23)
U.S. NFP	0.07	1.17^{*}	0.33
	(0.26)	(0.66)	(0.21)
U.S. RTS	0.31	1.76^{***}	0.87^{***}
	(0.26)	(0.68)	(0.22)
U.S. HGS	0.11	0.22	-0.04
	(0.28)	(0.69)	(0.22)
U.S. CCR	0.64^{**}	0.05	0.22
	(0.27)	(0.70)	(0.22)
U.S. MFI	0.59^{*}	0.59	0.30
	(0.34)	(0.79)	(0.25)
U.S. JBC	0.01	-0.73^{**}	-0.18^{*}
	(0.12)	(0.30)	(0.10)
U.S. DGO	-0.12	-0.08	-0.17
	(0.28)	(0.69)	(0.22)
FOMC PR: Certainty	-0.65^{***}	0.17	0.00
	(0.25)	(0.66)	(0.21)
FOMC PR: Optimism	-1.73^{***}	-0.16	-0.20
	(0.59)	(1.53)	(0.49)
FOMC PR: Pessimism	-0.02	1.36	0.14
	(0.37)	(0.95)	(0.31)
FOMC Minutes: Certainty	-0.70	-0.92	-0.32
	(0.57)	(1.27)	(0.41)
FOMC Minutes: Optimism	-2.38^{**}	-2.44	-0.95
	(1.09)	(2.48)	(0.79)
FOMC Minutes: Pessimism	-0.76	-0.74	-0.68
	(0.95)	(2.34)	(0.75)

(*continued*)

Table E8. (Continued)

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
U.S. Fed Purdah	−0.10	0.37	0.01
	(0.14)	(0.36)	(0.11)
DOM Press Release	0.25	0.04	0.12
	(0.35)	(0.89)	(0.29)
DOM Minutes Release	−0.39	−0.91	−0.06
	(0.42)	(1.02)	(0.33)
DOM PR: Certainty	0.36	0.11	0.20
	(0.42)	(1.10)	(0.35)
DOM PR: Optimism	0.40	−0.70	0.19
	(0.71)	(1.77)	(0.57)
DOM PR: Pessimism	−2.31***	1.11	1.02*
	(0.64)	(1.68)	(0.54)
DOM Minutes: Certainty	−0.74	0.82	0.19
	(0.84)	(1.60)	(0.51)
DOM Minutes: Optimism	−1.20	−4.72	−1.71
	(1.57)	(3.89)	(1.25)
DOM Minutes: Pessimism	−0.56	−1.23	−0.72
	(1.09)	(2.60)	(0.83)
DOM Purdah	0.11	−0.22	0.09
	(0.18)	(0.46)	(0.15)
Lag Dependent Variable	0.52***	0.52***	0.58***
	(0.01)	(0.02)	(0.02)
Constant	−0.06	−0.19	−0.05
	(0.07)	(0.18)	(0.06)
N	1,422	1,572	1,572
R^2-Adjusted	0.48	0.34	0.48

Table E9. Regression Results from Specification (2): Switzerland

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
FOMC Press Release	−0.20***	−0.30***	−0.03
	(0.07)	(0.09)	(0.03)
FOMC UMP Announcement	−0.09	0.14	−0.05
	(0.09)	(0.11)	(0.04)
FOMC Minutes Release	−0.08	−0.31***	−0.07*
	(0.09)	(0.11)	(0.04)
U.S. GDP	1.06	−1.31	−0.03
	(0.75)	(0.91)	(0.33)
U.S. EHS	0.43	−0.63	0.57*
	(0.76)	(0.89)	(0.33)
U.S. UNM	0.56	−0.76	0.38
	(0.76)	(0.88)	(0.32)
U.S. NFP	0.52	1.45*	0.23
	(0.66)	(0.82)	(0.30)
U.S. RTS	2.91***	0.64	0.67**
	(0.66)	(0.85)	(0.31)
U.S. HGS	0.81	0.04	0.01
	(0.73)	(0.86)	(0.31)
U.S. CCR	−0.57	−0.63	−0.64**
	(0.75)	(0.87)	(0.32)
U.S. MFI	1.02	−1.37	−0.12
	(0.78)	(0.98)	(0.36)
U.S. JBC	−1.18***	−0.75**	−0.17
	(0.32)	(0.38)	(0.14)
U.S. DGO	0.45	−0.54	0.08
	(0.76)	(0.86)	(0.31)
FOMC PR: Certainty	0.07	0.89	−0.19
	(0.69)	(0.82)	(0.30)
FOMC PR: Optimism	−1.69	−2.46	−0.28
	(1.52)	(1.92)	(0.70)
FOMC PR: Pessimism	0.36	−3.27***	−0.28
	(0.90)	(1.19)	(0.43)
FOMC Minutes: Certainty	0.05	−0.89	−0.03
	(1.50)	(1.59)	(0.58)
FOMC Minutes: Optimism	−1.29	−1.02	−0.22
	(2.81)	(3.10)	(1.13)
FOMC Minutes: Pessimism	−1.23	−1.67	0.12
	(2.46)	(2.92)	(1.06)

(*continued*)

Table E9. (Continued)

	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
U.S. Fed Purdah	0.20	−0.84*	−0.14
	(0.40)	(0.45)	(0.16)
DOM Press Release	−0.98	3.20**	0.12
	(1.13)	(1.31)	(0.48)
DOM PR: Certainty	1.51*	0.42	0.37
	(0.79)	(0.78)	(0.29)
DOM PR: Optimism	0.84	−1.78	0.03
	(1.50)	(1.90)	(0.69)
DOM PR: Pessimism	4.18**	−2.60	−0.59
	(1.66)	(1.83)	(0.67)
Lag Dependent Variable	0.41***	0.18***	0.47***
	(0.01)	(0.02)	(0.02)
Constant	0.00	−0.36*	−0.06
	(0.19)	(0.21)	(0.08)
N	1,092	1,572	1,572
R^2-Adjusted	0.71	0.10	0.34

Appendix F. U.S. Regression Results from Specification (2) Using Lewbel Model

Table F1 shows estimates for model (2) using Lewbel's (2012) method for identification via heteroskedasticity. FOMC press releases, meeting minutes releases, and unconventional monetary policy (UMP) announcements are instrumented using a function of the remaining variables in the model. U.S. surprise macroeconomic news variables include gross domestic product growth (GDP), existing home sales (EHS), unemployment rate (UNM), non-farm payroll (NFP), retail sales (RTS), housing starts (HGS), consumer credit (CCR), manufacturing index (MFI), jobless claims (JBC), and durable goods orders (DGO). *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table F1. U.S. Regressions Results from Specification (2) Using Lewbel Model

	Three-Month LIBOR-OIS Spread	One-Year OIS	Sovereign Bond Spread	Ten-Year Sovereign Bond Yield
FOMC Press Release	0.15	−0.05	−0.63***	−0.11***
	(0.12)	(0.07)	(0.14)	(0.04)
FOMC UMP Announcement	−0.23	−0.11	0.06	−0.09**
	(0.15)	(0.09)	(0.17)	(0.05)
FOMC Minutes Release	−0.04	−0.10	−0.04	−0.14***
	(0.15)	(0.08)	(0.18)	(0.05)
U.S. GDP	−0.47	1.11	0.35	0.31
	(1.11)	(0.69)	(1.24)	(0.34)
U.S. EHS	−1.51	0.49	0.77	0.22
	(1.07)	(0.68)	(1.22)	(0.34)
U.S. UNM	−0.84	0.29	0.93	0.34
	(1.09)	(0.67)	(1.26)	(0.35)
U.S. NFP	0.23	1.47**	0.43	0.25
	(1.04)	(0.63)	(1.18)	(0.33)
U.S. RTS	−0.69	1.73***	1.68	1.27***
	(1.07)	(0.65)	(1.19)	(0.33)
U.S. HGS	−0.78	−0.23	−1.31	−0.23
	(1.04)	(0.66)	(1.24)	(0.34)

(*continued*)

Table F1. (Continued)

	Three-Month LIBOR-OIS Spread	**One-Year OIS**	**Sovereign Bond Spread**	**Ten-Year Sovereign Bond Yield**
U.S. CCR	−0.63	0.19	0.22	0.22
	(1.11)	(0.67)	(1.34)	(0.37)
U.S. MFI	0.64	1.93***	−2.14	0.54
	(1.41)	(0.75)	(1.51)	(0.42)
U.S. JBC	0.55	−0.57**	−1.62***	−0.31**
	(0.47)	(0.29)	(0.54)	(0.15)
U.S. DGO	−0.79	−0.21	−0.39	−0.26
	(1.12)	(0.66)	(1.25)	(0.34)
FOMC PR: Certainty	0.08	0.77	0.73	−0.20
	(0.99)	(0.63)	(1.17)	(0.32)
FOMC PR: Optimism	0.53	1.69	−2.94	0.07
	(2.29)	(1.46)	(2.65)	(0.73)
FOMC PR: Pessimism	−0.05	0.50	3.53**	0.14
	(1.44)	(0.91)	(1.69)	(0.47)
FOMC Minutes:	2.01	−0.85	6.99**	0.46
Certainty	(2.74)	(1.21)	(2.89)	(0.80)
FOMC Minutes:	0.16	−0.46	14.85***	2.20
Optimism	(4.61)	(2.37)	(5.56)	(1.53)
FOMC Minutes:	−0.35	−0.54	8.11*	0.69
Pessimism	(4.31)	(2.23)	(4.77)	(1.32)
U.S. Fed Purdah	−0.82	−0.28	1.59**	0.08
	(0.55)	(0.34)	(0.63)	(0.17)
Lag Dependent	0.39***	0.45***	0.50***	0.40***
Variable	(0.03)	(0.02)	(0.02)	(0.02)
Constant	0.43	0.00	0.24	−0.01
	(0.27)	(0.16)	(0.32)	(0.09)
N	1,389	1,572	1,335	1,338
R^2-Adjusted	0.15	0.22	0.30	0.25
Cragg-Donald F-Stat	130.02	316.41	163.68	145.68
(Stock-Yogo Critical Value at 5% Maximal IV Relative Bias)	(20.73)	(20.73)	(20.73)	(20.73)

Appendix G: Regressions Results from Specification (3)

In tables G1–G3, estimates for model (3) with standard errors are shown in parentheses. U.S. estimation uses robust least squares; estimation for systemically important advanced economies (SIAEs) and small open advanced economies (SOAEs) use fixed effects with clustered standard errors. Only the coefficient estimates on the monetary policy surprises in the U.S. (MPS^{US}) and U.S. FOMC communications content (C^{US}) are reported; see appendix C for a full list of control variables included in the regressions. $I(MPS^2)$ is a Heaviside variable equal to one when the policy surprise variable (second principal component of U.S. MPS) is positive, and zero otherwise. *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table G1. Regressions Results from Specification (3): United States

	Three-Month LIBOR-OIS Spread	One-Year OIS	Bond Spread	Ten-Year Yield
Press Release	−0.06	−0.05	−0.53***	−0.14***
	(0.07)	(0.05)	(0.10)	(0.03)
UMP Announcement	−0.03	−0.06	0.10	−0.02
	(0.09)	(0.06)	(0.12)	(0.04)
Minutes Release	0.06	0.04	−0.29**	−0.12***
	(0.10)	(0.06)	(0.14)	(0.04)
PR: Certainty	0.37	0.43	−1.23	−0.21
	(1.00)	(0.74)	(1.37)	(0.44)
$I(MPS^2)$*PR: Certainty	0.53	−0.72	−0.98	0.03
	(1.26)	(0.93)	(1.74)	(0.56)
PR: Optimism	−0.84	1.12	−8.12***	−1.09
	(2.12)	(1.58)	(2.90)	(0.93)
$I(MPS^2)$*PR: Optimism	1.83	−3.89*	11.40***	2.31*
	(2.91)	(2.16)	(3.97)	(1.27)
PR: Pessimism	−2.40**	−0.14	−6.46***	−0.70
	(1.09)	(0.80)	(1.48)	(0.47)
$I(MPS^2)$*PR: Pessimism	3.47*	4.29***	16.00***	2.96***
	(2.10)	(1.56)	(2.98)	(0.95)
Minutes: Certainty	2.00	−0.47	1.19	0.45
	(1.74)	(0.90)	(2.20)	(0.70)
Minutes: Optimism	−2.07	0.90	6.46	1.03
	(2.93)	(1.75)	(4.23)	(1.35)
Minutes: Pessimism	0.30	0.47	1.41	1.14
	(2.73)	(1.65)	(3.63)	(1.16)
N	1,389	1,572	1,335	1,338
R^2-Adjusted	0.28	0.30	0.36	0.30

Table G2. Regressions Results from Specification (3): SIAEs

	Three-Month LIBOR-OIS Spread	One-Year OIS	Bond Spread	Ten-Year Yield
Press Release	−0.05	−0.15	−0.16	−0.07**
	(0.07)	(0.07)	(0.14)	(0.01)
UMP Announcement	0.20	−0.05	−0.11	−0.05***
	(0.13)	(0.04)	(0.09)	(0.01)
Minutes Release	−0.12	−0.22	−0.12	−0.06*
	(0.06)	(0.11)	(0.17)	(0.02)
PR: Certainty	0.69	2.74	0.11	0.17
	(4.01)	(2.85)	(0.93)	(0.08)
I(MPS^2)*PR: Certainty	−0.90	−3.29	0.43	−0.02
	(3.74)	(2.86)	(1.53)	(0.11)
PR: Optimism	2.32	−1.66***	−1.75	−0.34
	(6.04)	(0.13)	(1.62)	(0.24)
I(MPS^2)*PR: Optimism	−0.92	2.59	0.17	−0.19
	(7.13)	(2.48)	(1.09)	(0.46)
PR: Pessimism	4.29	0.33	−1.55*	−0.64*
	(3.57)	(0.56)	(0.50)	(0.21)
I(MPS^2)*PR: Pessimism	−4.87	2.69	4.26*	1.40
	(4.15)	(0.98)	(1.53)	(0.63)
Minutes: Certainty	3.76	−1.58	−1.06	−0.57
	(7.29)	(1.02)	(1.33)	(0.42)
Minutes: Optimism	−2.72	−4.97	−3.86	−1.27*
	(8.82)	(3.31)	(3.66)	(0.49)
Minutes: Pessimism	5.61	−2.19	1.31	−0.26
	(10.23)	(1.62)	(2.03)	(0.46)
N	4,906	3,942	5,460	6,036
R^2-Adjusted	0.05	0.13	0.12	0.26

Table G3. Regressions Results from Specification (3): SOAEs

	Three-Month LIBOR-OIS Spread	One-Year OIS	Bond Spread	Ten-Year Yield
Press Release	−0.15**	−0.02	−0.22	−0.06***
	(0.03)	(0.01)	(0.10)	(0.01)
UMP Announcement	0.14	−0.02	−0.03	−0.04*
	(0.06)	(0.03)	(0.06)	(0.02)
Minutes Release	0.06	−0.06	−0.26***	−0.06***
	(0.06)	(0.03)	(0.03)	(0.01)
PR: Certainty	2.36**	0.17	−0.40	1.08
	(0.65)	(0.08)	(0.23)	(1.15)
I(MPS^2)*PR: Certainty	−2.54*	−0.02	0.00	−1.70
	(0.94)	(0.11)	(0.28)	(2.62)
PR: Optimism	4.38**	−0.34	−0.75	−0.60
	(1.29)	(0.24)	(0.43)	(1.29)
I(MPS^2)*PR: Optimism	0.15	−0.19	−0.24	1.18
	(3.63)	(0.46)	(0.64)	(2.51)
PR: Pessimism	3.99***	−0.64*	0.15	−0.94
	(0.54)	(0.21)	(0.12)	(1.08)
I(MPS^2)*PR: Pessimism	−3.55	1.40	0.70	5.30*
	(5.25)	(0.63)	(0.61)	(1.96)
Minutes: Certainty	0.58	−0.57	−0.23	−1.52
	(1.13)	(0.42)	(0.13)	(1.39)
Minutes: Optimism	1.90	−1.27*	−0.06	−2.67
	(2.63)	(0.49)	(0.51)	(1.83)
Minutes: Pessimism	0.83	−0.26	−1.16**	0.20
	(1.82)	(0.46)	(0.26)	(0.62)
N	5,122	7,515	6,522	7,479
R^2-Adjusted	0.10	0.31	0.25	0.32

References

Lewbel, A. 2012. "Using Heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models." *Journal of Business and Economic Statistics* 30 (1): 67–80.

Loughran, T., and B. McDonald. 2011. "When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks." *Journal of Finance* 66 (1): 35–65.

Estimating a Phillips Curve for South Africa: A Bounded Random-Walk Approach*

Alain Kabundi,[a] Eric Schaling,[b] and Modeste Some[c]
[a]World Bank
[b]University of the Witwatersrand and VU University Amsterdam
[c]International Monetary Fund

In this paper we estimate a Phillips curve for South Africa using a bounded random-walk model. Central bank credibility, the slope of the Phillips curve, the natural rate of unemployment, and the central bank's inflation target band are time varying. We find that the slope of the Phillips curve has flattened since the mid-2000s—particularly after the Great Recession—which is in line with the findings in most advanced countries. Our results do not lend support to the hypothesis that the ability of the South African Reserve Bank to hit its inflation target has decreased. With respect to the faith in the IT regime as measured by the degree to the extent of which inflation expectations are anchored to the target, our results indicate that inflation persistence has increased from 1994 to 2001, remained constant from 2001 to 2008, and eventually increased around 2008. This pattern is different from that of advanced countries where expectations have become better anchored relatively early in the IT regime. Moreover, we find that the increased stability of inflation expectations after 2008—which coincides with the Great Financial Crisis—is not only a result of good policy but also of "good luck."

JEL Codes: C51, E52, E58.

*The views expressed in this paper are those of the author(s) and do not necessarily represent those of the World Bank or the International Monetary Fund. We are grateful to two anonymous referees, Loretta Mester, Laura Papi, Nicola Viegi, and Yi Wu for constructive comments and suggestions. Financial support from ERSA is gratefully acknowledged. Author e-mails: akabundi@worldbank.org, Eric.Schaling@wits.ac.za, and msome@imf.org.

1. Introduction

The relationship between inflation and activity which was dubbed the “Phillips” curve by Samuelson and Solow (1960), following the celebrated contribution by Phillips (1958), remains one of the cornerstones of modern macroeconomics. For example, it features prominently in rational expectations guise in New Keynesian models such as Galí, Smets, and Wouters (2012) and Galí (2015a).

On the fiftieth anniversary of Phillips’ paper, Gordon (2011) provides a roadmap of its evolution since 1975. According to Gordon (2011), in the post-1975 era, the Phillips curve has evolved into two strands: a “left fork” and a “right fork.” The left fork constitutes a framework that allows policy to respond to shocks in the context of price stickiness. This involves an inflation model where expectations are backward looking. The “left fork road” emphasizes the role of demand shock, inflation inertia, and supply shocks in explaining the dynamics in inflation. Demand shocks are proxied by the unemployment gap, whereas supply shocks include variables such as changes in the relative prices of food, energy, and imports. And inflation inertia is represented by the formation of expectations and persistence due to fixed duration in wage and price contracts. The New Keynesian model follows the right fork whereby, in line with rational expectations versions of the Phillips curve, forward-looking expectations can jump in response to policy changes.[1]

A recent contribution by Blanchard, Cerutti, and Summers (2015)—clearly along the left fork of the road—investigates the relationship between output, unemployment, and inflation over the course of about fifty years for twenty-three advanced economies. They estimate for each country a benchmark relation between inflation, long-term inflation expectations, lagged inflation, and the unemployment gap. Their specification allows for the natural rate of unemployment as well as the coefficients to change over time. Focusing on the Great Financial Crisis, they find that the shift to inflation targeting and stable inflation for the two decades preceding the crisis have led forecasts of future inflation to put less weight on past inflation and more weight on the perceived target of the central

[1]See Kydland and Prescott (1977) and Sargent (1980).

bank. In addition, they find that the slope of the Phillips curve has flattened over time—with much of the decrease taking place from the mid-1970s to the mid-1990s and the slope being insignificant for most countries today. This then leads to a puzzle and a potential challenge for inflation targeting. At the same time as inflation expectations have become more anchored, the ability of central banks to affect inflation through the unemployment gap has decreased. Put another way, the faith in the ability of central banks to achieve their target has increased, while the effectiveness of monetary policy has decreased.

In this paper we investigate this puzzle for South Africa. Accordingly we build a "left fork of the road" Phillips-curve model in unemployment–inflation space along the lines of Chan, Koop, and Potter (2016) (CKP). We allow the slope of the Phillips curve, the central bank's perceived inflation target, the natural rate of unemployment, and inflation persistence to be time varying and estimate the model with Bayesian methods using a Markov chain Monte Carlo algorithm. As in CKP, we constrain some of our state variables to be consistent with economic theory or with the structure of the South African economy. For example, the South African Reserve Bank's (SARB's) official inflation targeting band is 3–6 percent. Therefore, we constrain the central bank's perceived target to fall within this band. Moreover, since the inflation persistence parameter in our model is interpreted as a measure of the degree of central bank credibility, we constrain this parameter to be between 0 and 1, where 0 captures full credibility and 1 is complete lack of credibility. Thus, unlike CKP, we explicitly tie the inflation persistence parameter to private agents' inflation expectations formation process and link trend inflation with the central bank's perceived inflation target. The above interpretation allows us to extend Kabundi and Schaling (2013) (KS) and Kabundi, Schaling, and Some (2015) (KSS) with both a time-varying implicit inflation target (band) and evolving central bank credibility.

KS examine the relationship between inflation and inflation expectations in South Africa. They find that economic agents' inflation expectations largely depend on lagged inflation. This suggests that the South African Reserve Bank has not been successful in anchoring expectations of the private sector since the adoption of the inflation-targeting (IT) regime in 2000. They also find evidence that the SARB's implicit inflation target lies above the upper bound of the official IT band. KSS disaggregate KS and allow for three groups of agents in the model: financial analysts, trade unions, and business. Results of that paper indicate that expectations of price setters (business and unions) are closely related to each other and are higher than the upper bound of the official target band, while expectations of analysts are within the target band. Further, they find that the SARB has successfully anchored expectations of analysts but that price setters have not sufficiently used the focal point implicit in the IT regime.

However, neither KS nor KSS estimate a Phillips curve for South Africa in a time-varying parameter framework. This paper attempts to close this gap and, because of the richer framework, is able to answer several questions in the spirit of Blanchard, Cerutti, and Summers (2015) and Gillitzer and Simon (2015) such as: How has the slope of the Phillips curve evolved over time and what can be said about the faith in the IT regime as proxied by the evolving level of central bank credibility and the perceived inflation target? Has the ability of the central bank to hit its inflation target decreased?

Our results show that in South Africa inflation persistence and the slope of the Phillips curve are time varying. Specifically, the inflation persistence parameter has decreased since the Great Recession in 2008. This suggests that the SARB's credibility has increased since 2008. This is consistent with the view that inflation persistence has decreased since the 1980s and that the adoption of inflation targeting in most advanced economies has led to less persistent inflation. As for the slope parameter, results show that there is a slight decrease since 2008. This means that inflation has become less responsive to demand-side factors in South Africa. This is in line with the results of Matheson and Stavrev (2013) and Blanchard, Cerutti, and Summers (2015), who find that the slope of the Phillips curve in the United States and several OECD economies has significantly decreased since the 1980s.

The remainder of the paper is organized as follows: section 2 introduces the unobserved-components model. In section 3 we discuss the data, while our empirical results are given in section 4. Section 5 concludes and suggests avenues for further research.

2. The Unobserved-Components Model

The model we use is a standard unemployment-based Phillips curve (see, for example, Ball and Mazumder 2011, Matheson and Stavrev 2013, Ball 2015, and Gillitzer and Simon 2015). More specific, we assume that the economy is characterized by the following Phillips curve:[2]

$$\pi_t = \pi_t^e - \alpha_t(u_t - u_t^n) + \varepsilon_t, \tag{1}$$

where π_t is the inflation rate between time $t-1$ and t, π_t^e is expected inflation, u_t is the time-t unemployment rate, α_t is the slope of the Phillips curve which is allowed to be time varying, and ε_t is a residual capturing other factors such as supply (cost-push) shocks. To account for this fact, we specify a stochastic process for the conditional volatility of the disturbance term ε_t in the Phillips curve as

$$\varepsilon_t \rightsquigarrow N(0, h_t^2)$$
$$\log(h_t) = \log(h_{t-1}) + \varepsilon_t^h,$$

where ε_t^h is an iid process with mean 0 and variance σ_h^2 and uncorrelated with ε_t. We also assume that each error term is uncorrelated with the others. Here u_t^n is the natural rate of unemployment that prevails when inflation is equal to expected inflation ($\pi_t = \pi_t^e$) and when shocks are absent ($\varepsilon_t = 0$).[3]

Note that in equation (1) the variable u_t^n is unobserved. Moreover, we need to make an assumption about how inflation expectations are formed in (1) to fully describe the dynamics of inflation. Kabundi, Schaling, and Some (2015) model inflation expectations in South Africa as a weighted average of lagged inflation and the South African Reserve Bank's (SARB) implicit inflation target.[4] We follow

[2]Ball and Mazumder (2011, p. 346) define core inflation as the part of inflation explained not by supply shocks, but rather by expected inflation and economic activity. Thus in equation (1) core inflation can be written as $\pi_t^c = \pi_t^e - \alpha_t\,(u_t - u_t^n)$.

[3]For u_t^n to be well identified, we will impose $\alpha_t > 0\ \forall$ t.

[4]More specifically, in Kabundi, Schaling, and Some (2015), inflation expectations are modeled as $\pi_t^e = \rho\pi_{t-1} + (1-\rho)\pi^*$, where the weight parameter ρ and the inflation target π^* are constant over time.

the same logic to specify the inflation expectations process. However, we take into account the fact that the inflation expectations formation process may vary over time. In fact, Kabundi, Schaling, and Some (2015) interpret the weight on lagged inflation as the parameter that captures the level of credibility of monetary policy. The idea is that the closer this weight is to zero, the better inflation expectations are anchored to the target. The credibility of monetary policy may change over time and thus we allow the weight on lagged inflation to be time varying. Moreover, the SARB does not have an explicit point target but instead has a target band of 3–6 percent. Thus, we assume that the SARB's implicit inflation target point is unobserved and is time varying. Accordingly, the inflation expectation process is given by

$$\pi_t^e = \rho_t \pi_{t-1} + (1 - \rho_t)\pi_t^*, \tag{2}$$

where π_t^* is a proxy for the SARB's inflation target point (in the spirit of Kabundi, Schaling, and Some 2015), which is assumed to be time varying. ρ_t is a time-varying parameter that captures the weight agents put on past inflation. As mentioned before, when $\rho_t = 0$, inflation expectations are completely anchored to the central bank's inflation target ($\pi_t^e = \pi_t^*$). In this case the central bank policy is fully credible, whereas it totally lacks credibility when $\rho_t = 1$.[5]

The reason the SARB should focus on anchoring can be inferred from equations (1) and (2) of the paper. It has to do with the so-called second-round effects of the supply shock ε_t. Via equation (1) an adverse shock to inflation raises the actual inflation rate in the same period. Then (assuming $0 < \rho < 1$) inflation expectations for time $t+1$ increase. These in turn raise inflation in period $t+1$. This is the second-round effect. Of course, the feedback loop does not stop here and goes on indefinitely. What can be seen from equation

[5]See Kabundi, Schaling, and Some (2015) for further discussion on the link between ρ and central bank credibility. Using our notation, Matheson and Stavrev (2013) estimate $\pi_t^e = \rho_t \pi_{t-1}^4 + (1 - \rho_t)\bar{\pi}_t$, where $\bar{\pi}_t$ is long-run inflation expectations (sourced from the Federal Reserve Board) and $\pi_{t-1}^4$is year-over-year headline CPI inflation (lagged one quarter). Thus, they anchor inflation expectations to *long-run* inflation expectations, not to the central bank's inflation target. However, to the extent that the former are influenced by the Fed's (implicit) inflation target, our specification is not that dissimilar.

(2) is that if inflation expectations are fully anchored (i.e., if $\rho = 0$), there are no second-round effects.

We assume that π_t^* (unobserved) follows the random-walk process[6]

$$\pi_t^* = \pi_{t-1}^* + \varepsilon_t^*. \tag{3}$$

Combining equations (1), (2), and (3), the reduced form of the inflation process can be written as

$$\pi_t - \pi_t^* = \rho_t(\pi_{t-1} - \pi_{t-1}^*) - \alpha_t(u_t - u_t^n) + \nu_t, \tag{4}$$

where $\nu_t = \varepsilon_t - \rho_t \varepsilon_t^*$, with variance $\sigma_{v,t}^2 = h_t + \rho_t^2 \sigma_{\varepsilon^*}^2$.[7]

Equation (4) is a Phillips curve in terms of the cyclical component of inflation (if we assume that the central bank target π_t^* is a good proxy for trend (or core) inflation). Basically, the dynamics of the cyclical component of inflation, $\pi_t - \pi_t^*$, are explained by built-in persistence due here to agents' expectations formation process; excess demand, $u_t - u_t^n$; and other supply shocks ν_t. This formulation of the Phillips curve based on cyclical inflation has been adopted in previous work, including Stock and Watson (2007), Stella and Stock (2013), and Chan, Koop, and Potter (2016). The difference with our specification is that we explicitly tie the persistence parameter ρ_t to economic agents' inflation expectations instead of just an ad hoc statistical parameter to be estimated.[8]

Note that when $(1 - \rho_t L)(\pi_t - \pi_t^*) = 0$ and $\nu_t = 0$, we have $u_t = u_t^n$ (where L is the lag operator). Thus, the expression for u_t^n as the natural rate of unemployment is slightly different from the traditional definition of the non-accelerating inflation rate of unemployment (NAIRU), where one only needs $\pi_t = \pi_{t-1}$. Our specification

[6]Note that the random-walk process was adopted to account for slow change in the inflation target.

[7]Note that the error term v_t in the reduced form of the inflation equation (4) is correlated with the error term of the inflation target equation (3) ε_t^*, as $cov(v_t, \varepsilon_t^*) = cov(\varepsilon_t - \rho_t \varepsilon_t^*, \varepsilon_t^*) = -\rho_t \sigma_{\varepsilon^*}^2$. Note that independence between the two terms can be reasonably assumed if the $\rho_t \sigma_{\varepsilon^*}^2$ term is negligible (both terms of the product are between 0 and 1), which appears to be the case in South Africa since $\sigma_{\varepsilon^*}^2$ is small (we estimate it at 0.003).

[8]For a recent specification related to our work, see Blanchard, Cerutti, and Summers (2015).

does not explicitly include a supply shock variable as an explanatory factor in the Phillips curve, and thus differs somewhat from the triangle specification of Gordon (1998).[9] However, as said before, we allow the residual ν_t to follow a stochastic volatility process to correct for potential heteroskedasticity introduced by the omission of supply-side variables.

We assume that the parameters ρ_t and α_t follow random-walk processes

$$\rho_t = \rho_{t-1} + \varepsilon_t^{\rho} \tag{5}$$

$$\alpha_t = \alpha_{t-1} + \varepsilon_t^{\alpha}, \tag{6}$$

where ε_t^{ρ} and ε_t^{α} are error terms whose processes will be made clear shortly.

Since the natural rate of unemployment, u_t^n, is unobserved, the cyclical unemployment $u_t - u_t^n$ is unobserved as well. Following Chan, Koop, and Potter (2016), we specify an AR(2) process for cyclical unemployment as follows:

$$u_t - u_t^n = \varphi_1(u_{t-1} - u_{t-1}^n) + \varphi_2(u_{t-2} - u_{t-2}^n) + \varepsilon_t^u, \tag{7}$$

where φ_1 and φ_2 are constant parameters and ε_t^u is an identically independently distributed (iid) error term with mean 0 and variance σ_u^2.[10] Since we want to use inflation and unemployment data to estimate the model, we also specify a process for the natural rate of unemployment as a random-walk process:[11]

$$u_t^n = u_{t-1}^n + \varepsilon_t^n, \tag{8}$$

where ε_t^n is the error term to be defined below. Note that this specification of the natural rate discards the possibility of the hysteresis hypothesis of unemployment where the natural rate of unemployment depends on past unemployment rates.[12]

---

[9] For an analysis about optimal monetary policy in a triangle model, see Bullard and Schaling (2001).

[10] In a preliminary analysis, we find that, using a Hodrick-Prescott (HP) filter, the cyclical unemployment follows an AR(2) process and there is no evidence of time variation of the coefficients φ_1 and φ_2. Matheson and Stavrev (2013) assume that the persistence of the unemployment gap is constant.

[11] Equation (8) allows for a slow variation in the NAIRU from one quarter to another.

[12] For a recent analysis of unemployment hysteresis, see Galí (2015b).

Although supply shocks such as cost-push pressure by unions or "oil sheiks" are not explicitly modeled, we stress that our Phillips-curve model is close to the "left fork of the road" (Gordon 2011) or econometrically sound mainstream triangle approach (as opposed to the "right fork" or rational expectations approach). This can be seen by combining (4) and (7). This yields

$$\pi_t = \rho_t L\pi_t - \alpha_t \left(\varphi_1 L + \phi_2 L^2\right)(u_t - u_t^n) + (1 - \rho_t L)\pi_t^* - \alpha_t \varepsilon_t^u + \nu_t. \tag{9}$$

This expression is similar to equation (13) of Gordon (2011).

The system of equations (4), (3), (5), (6), (7), and (8) can be viewed as a bivariate unobserved-components model of inflation and unemployment where the parameters ρ_t and α_t are time varying.

Note that without further restrictions on the state variables u_t^n, π_t^*, ρ_t, and α_t and with the standard distributional assumptions on the error terms, this system can be estimated using a Kalman-filter algorithm. However, this would mean that these variables are in principle unbounded when the variances of the error terms are significantly large. We depart from this assumption for the following reasons. First, the SARB has a clearly specified inflation target range between 3 and 6 percent. Even if a target point is not clearly specified, it would not be reasonable to assume that the SARB's unobserved target point π_t^* can take any value. Therefore we have to impose a restriction of the type $3\% \leq \pi_t^* \leq 6\%$ at any time t. Second, here the inflation persistence parameter ρ_t in (4) captures the perceived credibility of monetary policy or the extent to which inflation expectations are anchored. Perfect credibility is associated with $\rho_t = 0$, whereas a complete lack of credibility implies $\rho_t = 1$ with imperfect credibility in between. So here, a priori, we have the constraint $0 \leq \rho_t \leq 1$.

A preliminary analysis using an HP filter shows that the cyclical component of unemployment follows a stationary AR(2) process. This implies that the parameters φ_1 and φ_2 in equation (7) must satisfy $\varphi_1 + \varphi_2 < 1$, $\varphi_1 - \varphi_2 < 1$ and $-1 < \varphi_2 < 1$. Moreover, the natural rate of unemployment is a steady-state concept and should be bounded. Finally, the Phillips-curve slope parameter α_t should be positive on theoretical grounds.

In general the random-walk trend variables in this model are bounded from below and above as

$$a_x \leq x_t \leq b_x, \tag{10}$$

where $x_t = u_t^n, \pi_t^*, \rho_t, \alpha_t$, and a_x and b_x are constant real numbers. Using the random-walk property of these variables, the inequalities in equation (10) imply that

$$a_x - x_{t-1} \leq \varepsilon_t^x \leq b_x - x_{t-1}, \tag{11}$$

where $\varepsilon_t^x = \varepsilon_t^n, \varepsilon_t^*, \varepsilon_t^\rho$, and ε_t^α.

Thus, for the boundedness restrictions of the random-walk processes to be satisfied in (3), (5), (6), and (8), we can simply bound the error terms below and above by time-varying bounds. Chan, Koop, and Potter (2016) use a similar framework to study inflation and unemployment trends for the U.S. economy. Matheson and Stavrev (2013) and Blanchard, Cerutti, and Summers (2015) estimate a similar Phillips curve with time-varying coefficients for twenty OECD countries where the slope coefficient and the inflation persistence parameter are constrained. As in Chan, Koop, and Potter (2016), we assume that the error terms $\varepsilon_t^x = \varepsilon_t^n, \varepsilon_t^*, \varepsilon_t^\rho$ follow a truncated normal distribution, that is, we have

$$\varepsilon_t^x \rightsquigarrow TN(a_x - x_{t-1}, b_x - x_{t-1}, 0, \sigma_x^2),$$

where $TN(\theta, \beta, \mu, \sigma^2)$ is the normal distribution of mean μ and variance σ^2 and truncated within $[\theta \quad \beta]$.

We estimate several parameters of the model by a Bayesian method. Let the time-invariant parameters be summarized in the following vector:

$$\psi = (\varphi_1, \varphi_2, \sigma_u^2, \sigma_h^2, \sigma_{u^n}^2, \sigma_{\pi^*}^2, \sigma_\rho^2, \sigma_\alpha^2, a_{u^n}, a_{\pi^*}, a_\rho, a_\alpha, b_{u^n}, b_{\pi^*}, b_\rho, b_\alpha)'.$$

Note that the bounded parameters can be fixed or estimated. During the estimation, we will fix the bounded parameters $a_\rho, b_\rho, a_\alpha, b_\alpha$ and estimate the inflation target and the natural rate of unemployment bounded parameters a_{π^*}, a_{u^n}, and b_{π^*}, b_{u^n}, respectively. So, the parameter vector to be estimated becomes $\psi = (\varphi_1, \varphi_2, \sigma_u^2, \sigma_h^2, \sigma_{u^n}^2, \sigma_{\pi^*}^2, \sigma_\rho^2, \sigma_\alpha^2, a_{u^n}, a_{\pi^*}, b_{\pi^*}, b_{u^n})'$.

With these "boundedness" restrictions, the model is highly nonlinear and standard Kalman-filter algorithms do not apply. We follow the algorithm proposed by Chan, Koop, and Potter (2016) to estimate the model. The algorithm is a Bayesian estimation method using a Markov chain Monte Carlo (MCMC) drawing procedure which takes into account the restrictions imposed on the state variables.

Before we give a brief summary of the algorithm, some notation needs to be introduced. For each variable z, we denote by $z = (z_1, z_2, \ldots, z_T)^{'}$ the sample vector of z where T is the sample size and $y = (\pi^{'}, u^{'})^{'}$. After specifying the priors for the parameters vector ψ and the initial state variables, the drawing procedure is a six-step MCMC algorithm and can be summarized as follows:

1. $p(\pi^* | y, u^n, \rho, \alpha, h, \psi)$
2. $p(u^n | y, \pi^*, \rho, \alpha, h, \psi)$
3. $p(\rho | y, \pi^*, u^n, \alpha, h, \psi)$
4. $p(\alpha | y, \pi^*, u^n, \rho, h, \psi)$
5. $p(h | y, \pi^*, u^n, \rho, \alpha, \psi)$
6. $p(\psi | y, \pi^*, u^n, \rho, \alpha, h)$

For the specification of the priors, we assume that all the standard deviations follow inverse gamma (IG) distributions, the bounded parameters $a_{\pi^*}, b_{\pi^*}, a_{u^n}, b_{u^n}$ follow uniform distributions, and the AR(2) parameters φ_1, φ_2 follow normal distributions. The initial state variables u_0^n, π_0^* , ρ_0, α_0 follow truncated normal (TN) distributions. In general, we use relatively non-informative priors in the analysis. To save space, we do not present here all the details of the algorithm and refer the reader to Chan, Koop, and Potter (2016) for a detailed description of the drawing procedure of each of the six steps above.

3. Data Analysis

The analysis uses quarterly unemployment rate data obtained from the South African Reserve Bank (SARB) covering the period

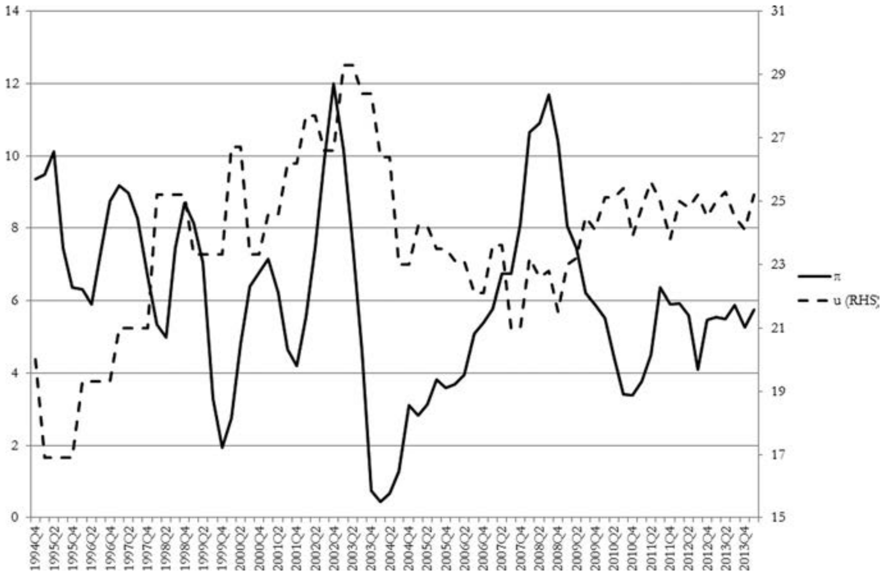
1994:Q1 to 2014:Q1. It is important to note that labor market data in South Africa are somewhat unreliable. Therefore, the sample size is determined by the availability of the unemployment data. The SARB constructs the unemployment time series by linking different labor surveys conducted by Statistics South Africa (Stats SA) from 1994 to most recent. In addition, the weights used in the different surveys are different. The first sample, from 1994 to 1999, is based on the annual October household survey. From 2000 to 2007 both the frequency and the approach used changed. The new sample is biannual, and it is based on the Labour Force Survey (LFS). Finally, from 2008 to present Stats SA publishes quarterly series of unemployment based on the Quarterly Labour Force Survey (QLFS). The QLFS is a household-based survey on the labor market activities of population aged fifteen to sixty-four years. It uses the strict definition of unemployment, that is, it does include discouraged jobseekers.

We emphasize that this is the only available unemployment series for South Africa that goes as far back as 1994. The current analysis necessitates an adequate number of observations in order to obtain statistically meaningful results. Moreover, starting in 1994 enables the analysis of the evolution of the Phillips curve before and during the inflation-targeting (IT) regime, which started in 2000. Viegi (2015) avoids altogether using the unemployment series in the estimation of his Phillips curve and instead uses the more reliable employment series. However, the unemployment rate is an essential variable especially for policymaking. It is crucial for the monetary policy authority to have an idea of the nature of relationship between inflation and unemployment. In addition, the estimation of the non-accelerating inflation rate of unemployment (NAIRU) is important for the conduct of monetary policy.

For inflation we use the year-on-year headline inflation data obtained from the South African Reserve Bank. However, we are aware that from 2000 to 2008 the SARB was targeting CPIX-inflation instead of the headline CPI.[13] In 2008 the SARB reverted back to targeting headline CPI inflation. We use headline CPI

[13] CPIX refers to headline CPI excluding mortgage costs.

Figure 1. Unemployment and Inflation



inflation to avoid statistical issues such as structural breaks that are inherent when two different series are used.[14]

Figure 1 depicts the unemployment and inflation rates from 1994:Q4 to 2014:Q1. It is clear from the figure that unemployment displays a discrete pattern from 1994 to 2007. The series becomes continuous from 2008 until the end of the sample. In 1994:Q4 South Africa registered its lowest unemployment rate at 16.9 percent. During this period inflation was around 10 percent. Then unemployment increased markedly, attaining the maximum of 29.3 percent in 2003:Q2. At the same time, inflation decreased first and reached its minimum value of 1.9 percent in 1999:Q4, then reversed sharply and reached a maximum of 12.00 percent in the second quarter of 2002. The rise in inflation was mainly due to a strong depreciation of the South African rand. Interestingly, the two series trend upwardly in early 2000 until late 2002; then inflation declined first, followed by

[14]The results are qualitatively the same when we use both the headline CPI inflation and the CPIX inflation.

unemployment. Hence, the graphical representation points to evidence of a Phillips curve in the beginning of the sample, but the curve flattened in the early part of 2000 until the later part of 2003 when the negative relationship recurred again all the way to the end of the sample. The surge in inflation in 2004 was caused by many factors—among others, an increase in demand, the rise in petrol price, and food prices. Unemployment decreased and reached a minimum of 21 percent in the fourth quarter of 2007; in the meantime, inflation peaked at 11.69 percent in 2008:Q3. The trend reversed when the impact of the financial crisis in the United States spilled over to South Africa, driving the economy into recession, which subsequently pushed unemployment to about 25 percent, and at the same time inflation plummeted to 3.39 percent in 2010:Q4 before stabilizing around the 6 percent level. The analysis based on the graphical representation of these two variables points to the changing nature of the Phillips curve in South Africa.

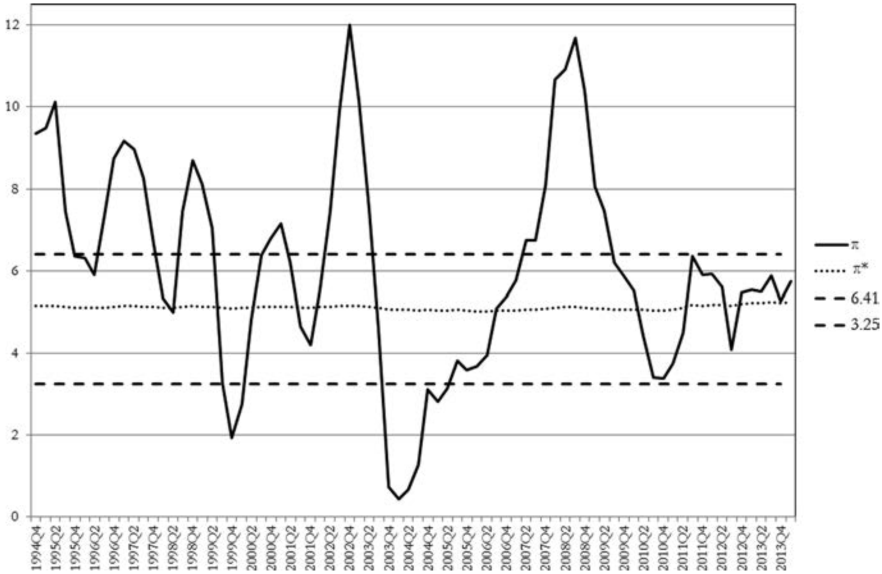
4. Empirical Results

This section presents the results obtained by estimating equation (4). We first discuss the extracted trends which represent, on the one hand, the implicit inflation target and the estimated target band and, on the other hand, the trend unemployment rate or NAIRU. Secondly, we discuss the relationship between the inflation cycle and the unemployment cycle. The empirical section concludes with the analysis of the estimated parameters—among others, inflation persistence, the slope of the Phillips curve, and lastly the conditional volatility of inflation.

4.1 Trend Inflation and Trend Unemployment

The estimated trends of inflation and unemployment from the state-space model follow a bounded random-walk process. The initial values are set in a way that is consistent with the two series. We set trend inflation between 3 percent and 7 percent, and trend unemployment between 15 percent and 30 percent. Figure 2 represents inflation together with the implicit inflation target and the estimated target bands. Interestingly, the estimated band is consistent with the official target between 3.25 percent and 6.41 percent. The

Figure 2. Inflation, Implicit Inflation Target, and Implicit Target Bands

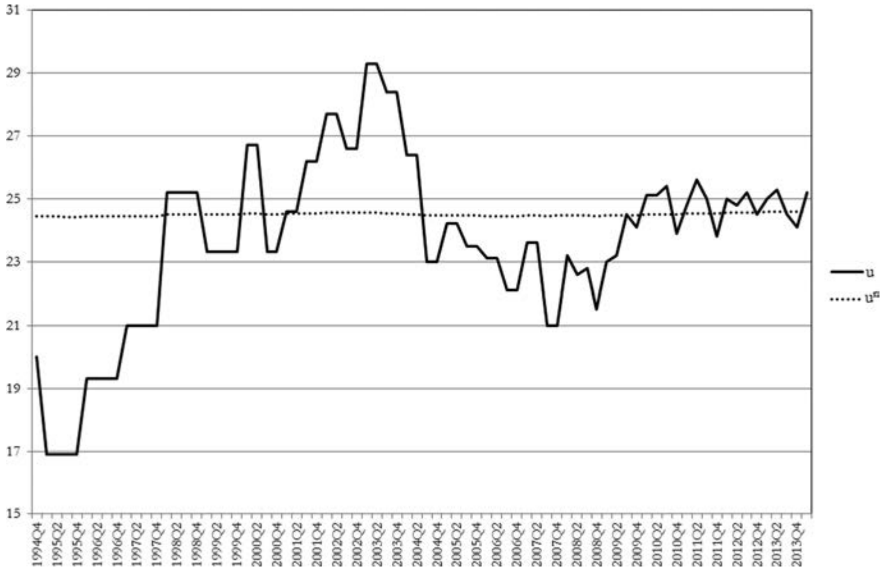


estimated inflation target (π^*) is relatively constant with a mean of 5.12 percent, and maximum and minimum values of 5.25 percent and 5.03 percent, respectively. These results are consistent with an implicit target of financial analysts of 5.51 percent, estimated by Kabundi, Schaling, and Some (2015). Note that Kabundi, Schaling, and Some (2015) use a different sample, from 2000 to 2013. Unlike these authors, the approach used in this paper allows the estimation of the target band. It is not surprising that the mean of the target is in line with the midpoint of the estimated band—in this case, 5 percent.

Similarly, the estimated unemployment trend (u^n) or NAIRU in figure 3 is relatively flat throughout the entire sample period, around 24.5 percent. Previous work suggests that the NAIRU for South Africa is about 25 percent.[15] Figure 7 in the appendix shows that the NAIRU estimated using the Phillips curve (PC) is slightly different from the estimation obtained from an atheoretical approach—in this

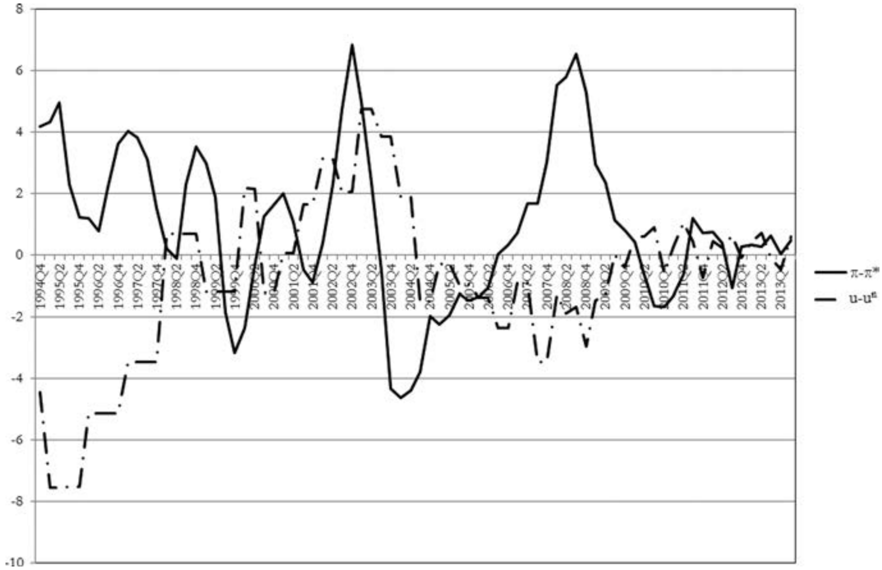
[15]See, for example, Viegi (2015).

Figure 3. Unemployment and NAIRU



case, an AR(2) process. The PC estimates are consistently higher than the AR ones and the difference widens from 2008:Q4 onward. Figure 3 shows that the unemployment rate was lower than the NAIRU from 1994 to 1998. This period corresponds to rising economic activity in South Africa. Then unemployment stabilizes somewhat around the NAIRU from 1998:Q2 to 2001:Q1. From 2001:Q2 the unemployment rate rises markedly way above the NAIRU and stays high for approximately three years. During this period the economy was weak, with a negative output gap. And from 2004:Q3 until the recent financial crisis the economy was at an expansionary stage and hence it created more jobs. Consequently, unemployment decreased below the NAIRU for about five years. The financial crisis pushed the South African economy into recession in 2009, which at the same juncture exerted pressure on unemployment, which rose back to the level of the NAIRU and has remained stable ever since. The persistent high level of unemployment at the end of the sample closely mimics weak economic activity in South Africa since the financial crisis.

Figure 4. Cyclical Components



4.2 Cyclical Components

In order to get some perspective on the Phillips curve in South Africa, in figure 4 we show the relationship between the cyclical components of inflation (inflation gap) and unemployment (unemployment gap) inferred from the model. According to equation (4), the Phillips-curve relationship involves the cyclical components of inflation and unemployment and not necessarily the levels as shown in figure 1. From figure 4 we can see the changing nature of the relationship between the two cycles for the period 1994–2014. There is evidence of a negative relationship between the two variables at the beginning of the sample, that is, from 1994:Q4 to 1998:Q1. The relationship becomes ambiguous from 1998:Q2 to 2001:Q3, which in turn is followed by a positive relationship between the two cyclical components. This result suggests that during this period of 1998:Q2–2001:Q3, the South African economy experienced stagflation whereby high cyclical inflation was explained by other factors than cyclical unemployment (see equation (4)). Note that the domestic currency (rand) depreciated significantly in 1998:Q2–2001:Q3.

That may explain a rise in inflation while at the same time the economy was subdued. The negative relationship between the two variables reemerges in 2004 and remains in existence but weakens somewhat towards the end the sample.

Importantly, the inflation gap seems more persistent than the unemployment gap. In addition, the inflation gap follows a long cycle, with a large amplitude from 2001 to 2008. Even if the 2001–02 cycle displays a large amplitude of 6.85 percent, it is short and lasts only a year. However, the 2002–08 cycle is both long and with a large amplitude, reaching a minimum of –4.63 percent. This cycle lasts four years and peaks in 2008:Q3 at 6.55 percent. From this finding it seems that the management of the inflation cycle was somewhat ineffective in reducing its length and/or its amplitude. The next section provides in-depth analysis of the dynamic nature of the Phillips curve, but also the persistence of the inflation cycle.

4.3 Parameters Estimates

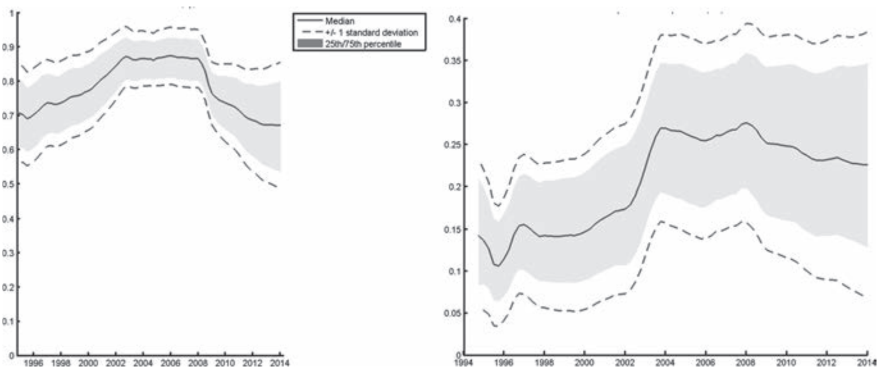
In this part, we present the results of the parameters estimates. As discussed in the model section, we fixed the bounded parameters during the estimation except the bounded parameters of inflation target a_{π^*}, b_{π^*}, and the natural rate of unemployment bounds a_{u^n}, b_{u^n}, which have been estimated.

We set $a_\rho = 0, b_\rho = 1$ in line with our interpretation of ρ as the degree of inflation expectations anchoring to the SARB inflation target. The slope of the Phillips-curve bounds are set as $a_\alpha = 0, b_\alpha = 1$. We draw 250,000 observations from the posterior distributions and discard the first 100,000 observations before computing the statistics.

The posterior estimates indicate that the inflation target bounds are slightly higher than the official SARB inflation target bounds. The estimate of the posterior median of the lower bound of the inflation target is $a_{\pi^*} = 3.25$, whereas the posterior median of the upper bound is estimated to be $b_{\pi^*} = 6.41$. The posterior median of the natural rate of unemployment lower and upper bounds are $a_{u^n} = 17.50$ and $b_{u^n} = 27.31$, respectively. The unemployment gap is very persistent, with estimated posterior means of the AR(2) coefficients $\varphi_1 = 0.86$ and $\varphi_2 = 0.007$. We present in the appendix

Figure 5. Inflation Persistence and Slope Parameters Estimates

A. Inflation Persistence (ρ_t) B. Slope of the Phillips Curve (α_t)



(table 1) some descriptive statistics of the posterior distributions and priors of the estimated constant parameters.

In a particular version of the model, we conduct the estimation without imposing the boundedness restrictions on the unobserved state variables and coefficients (u_t^n, π_t^*, ρ_t, α_t). However, then in some periods the estimated values of ρ_t and α_t lead to model instability. This highlights the importance of the restrictions imposed on ρ_t and α_t in this time-varying framework. Chan, Koop, and Potter (2016) find similar results for the U.S. economy. They find that bounding the random-walk processes (of the states), as in our case, yields better out-of-sample forecasts of inflation and unemployment compared with the unbounded case.

In figure 5 we present the smoothed estimates of ρ_t and α_t whereby the filtering is based on the full sample information. These two parameters are critical for the dynamics of inflation in the Phillips curve specified in equation (4). The parameter ρ_t captures the impact of inflation expectations on inflation, whereas the slope α_t captures the degree of the response of inflation to excess demand factors and the extent of the short-run tradeoff faced by policymakers. The more anchored inflation expectations are to the central bank target level π_t^*, the smaller ρ_t and the smaller the effect of inflation expectations on inflation. As shown in figure 5, our smoothed estimates suggest that the persistence parameter ρ_t is time varying and has increased from 1994 to 2001, remained constant from 2001 to 2008, and eventually declined after around 2008. This indicates that inflation expectations in South Africa have been relatively more anchored and stable since 2008.[16] Note, however, that the SARB's implicit target (π_t^*) estimates are consistent with financial market analysts' inflation expectations. Thus, this result would suggest that financial analysts' inflation expectations have been relatively more anchored than those of the price setters (unions and businesses) as found in Kabundi, Schaling, and Some (2015). Moreover, the financial crisis in 2008 followed by the recession in 2009 in South Africa open the question of whether this behavior of inflation expectations is the result of "good policy or good luck."

This can be formalized as follows. Lagging equation (1) by one period and substituting in (2), we get

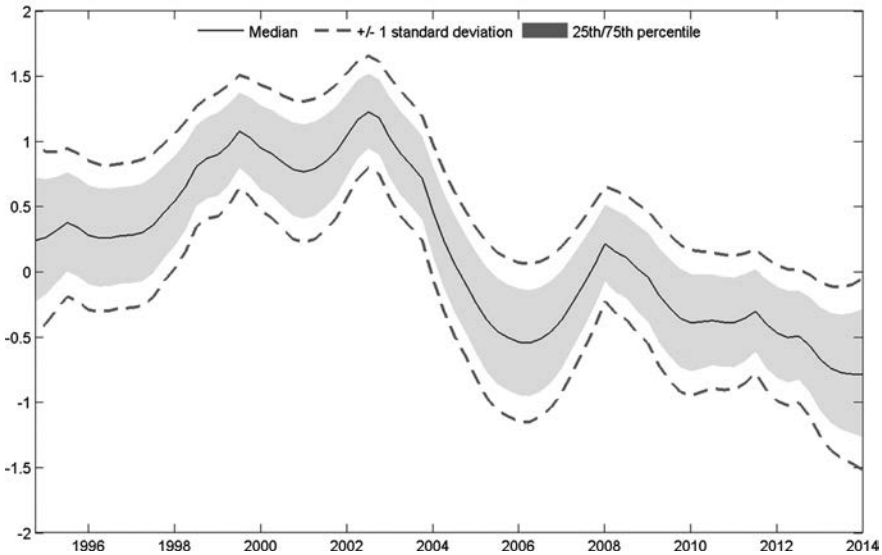
$$\pi_t^e = \frac{\rho_t}{1-\rho_t L}\left(\varepsilon_{t-1} - \alpha_{t-1}\left(u_{t-1} - u_{t-1}^n\right)\right) + \frac{1-\rho_t}{1-\rho_t L}\pi_t^*. \tag{12}$$

From this moving-average presentation of inflation expectations it can be seen that these are a weighted average of, on the one hand, the central bank's inflation target and, on the other hand, past cyclical unemployment and past supply shocks. The hypothesis of good policy (better anchoring of expectations) is supported by the data. We have seen a decline in ρ_t after 2008. However, independently of this development, figure 6 shows that there has also been a decrease in the conditional volatility of the inflation residual term around 2008 associated with a global decline in energy and food prices. This means that the variance of inflation has fallen. Thus the drop in inflation expectations was not only driven by good policy but also by good luck.

However, at lower levels, the slope parameter α_t has increased from 1994 to the mid-2000s and since then exhibits a slight downward trend. The decline in the slope parameter means that inflation

[16] Matheson and Stavrev (2013) find that during the 1970s inflation expectations became more backward looking and volatile. As the Federal Reserve began moving towards inflation targeting in the early 1980s, long-run inflation expectations began drifting downward and eventually settled at a lower level (around 2 percent) around 2000.

Figure 6. Inflation Residual Conditional Volatility ($\log(h_t)$)



has become less responsive to demand-side factors. In the context of our model, this suggests that the importance of unemployment as a driver of the inflation process has decreased. The implications for disinflation policy is that the sacrifice ratio (SR), which captures the increase in unemployment above the natural rate due to each percentage-point decline in inflation, is becoming higher.

However, it can also be shown that under an optimal inflation reduction policy (which balances inflation and unemployment costs) the SR decreases with better anchoring of inflation expectations. That suggests that the central bank should focus on anchoring of expectations which can be done by means of communicating a faster disinflation policy. More specific, Schaling and Hoeberichts (2010) show that in the context of a two-period version of the model of this paper (with rational private-sector learning) better anchoring (a lower value of ρ) positively depends on the prior probability that the private sector attaches to a quick disinflation. This result is consistent with Cogley, Primiceri, and Sargent (2010), who show that the persistence of the inflation gap (defined as the difference between inflation and the Federal Reserve's long-run target for inflation) fell after the Volcker disinflation.

There is a link between an increase in credibility, i.e., a decrease in ρ, and the flattening of the Phillips curve, i.e., a decrease in α. With high credibility, inflation tends to be constant around the implicit target, which implies that unemployment becomes uncorrelated with inflation. Then unemployment only reacts to the demand (supply) shock, while inflation remains relatively constant.[17]

5. Conclusion

In this paper we have estimated a Phillips curve for South Africa using a bounded random-walk model. Inflation persistence, the slope of the Phillips curve, the natural rate of unemployment, and the central bank's inflation target band were modeled as time-varying parameters and variable, respectively.

This framework has enabled us to answer several questions central to the conduct of monetary policy, such as the evolution of the slope of the Phillips curve, the faith in the IT regime as proxied by the evolving level of the inflation persistence, and the perceived inflation target (band).

Our results indicate that the slope of the Phillips curve has flattened since the mid-2000s—particularly after the Great Recession—which is in line with the findings in most advanced countries.

We find that our estimated inflation target band from 3.25 to 6.41 percent is slightly higher than the official SARB target bounds of 3–6 percent band per the inflation-targeting regime that has been in existence in South Africa since 2000. This suggests that monetary policy has been relatively loose and that there has been little attempt to hit the lower bound of the official band.

Related to the band is the central bank's perceived inflation target. The estimated target is relatively constant, with a mean of 5.12 percent. As it lies closer to the upper bound than the lower

[17]The flattening of the Phillips curve could also be due to forces of globalization. Trade and financial integration put downward pressure on domestic prices by increasing competition and productivity in such a way that domestic firms have less power in setting prices. Furthermore, with trade integration, domestic demand is more easily satisfied by imported goods, thereby making inflation less responsive to excess demand from the domestic country.

bound of the official target band, this may be indicative of some accommodation of cost-push shocks.

With respect to the faith in the IT regime as measured by the degree to the extent of which inflation expectations are anchored to the target, our results indicate that the inflation persistence has increased from 1994 to 2001, remained constant from 2001 to 2008, and eventually increased around 2008. This pattern is different from that of advanced countries where expectations have become better anchored relatively early in the IT regime. Moreover, we find that the increased stability of inflation expectations after 2008—which coincides with the Great Financial Crisis—is not only a result of good policy but also of "good luck."

Appendix

Figure 7. Atheoretical and Phillips Curve NAIRU

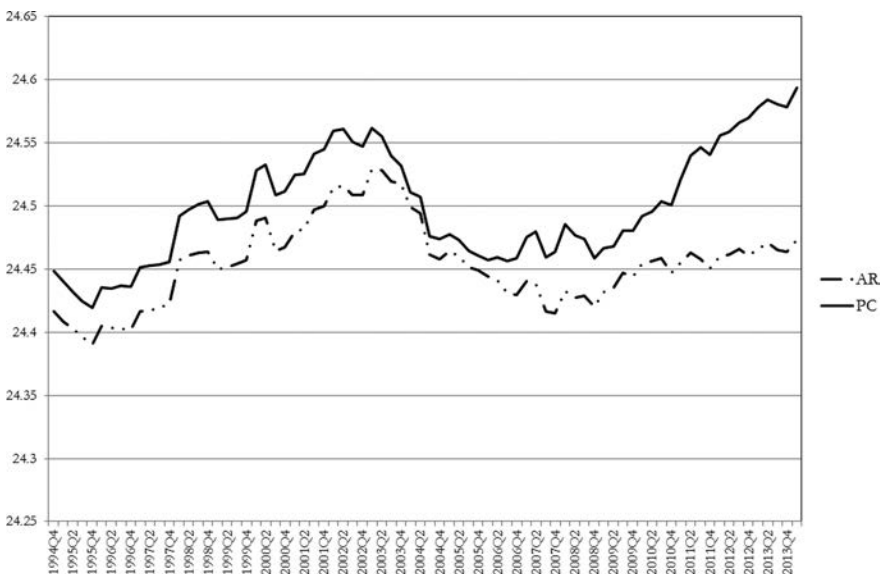


Table 1. Posterior Distribution Statistics and Priors

Parameter	Mean	Std.	Min.	Max.	Priors
φ_1	0.86	0.1	0.35	1.28	1.50
φ_2	0.01	0.1	−0.41	0.54	−0.50
σ_u^2	1.11	0.15	0.64	2.21	9.00
σ_h^2	0.10	0.02	0.042	0.28	1.80
$\sigma_{u^n}^2$	0.01	0.002	0.004	0.03	0.18
$\sigma_{\pi^*}^2$	0.02	0.005	0.008	0.07	0.36
σ_ρ^2	0.002	0.001	0.001	0.007	0.04
σ_α^2	0.002	0.001	0.001	0.006	0.04
a_{u^n}	17.50	1.45	15	20	20
a_{π^*}	3.25	0.14	2.98	3.50	4.50
b_{π^*}	6.41	0.40	5.50	7.03	6.00
b_{u^n}	27.40	1.42	25	30	26

References

Ball, L. 2015. "Comment on 'Inflation and Activity' by Olivier Blanchard, Eugene Cerutti and Lawrence Summers." ECB Forum on Central Banking, Sintra, Portugal, May 21–23.

Ball, L., and S. Mazumder. 2011. "Inflation Dynamics and the Great Recession." *Brookings Papers on Economic Activity* 42 (Spring): 337–405.

Blanchard, O., E. Cerutti, and L. Summers. 2015. "Inflation and Activity — Two Explorations and their Monetary Policy Implications." Paper presented at the ECB Forum on Central Banking, Sintra, Portugal, May 21–23.

Bullard, J., and E. Schaling. 2001. "New Economy—New Policy Rules?" *Quarterly Review* (Federal Reserve Bank of St. Louis) 83 (5, September/October): 57–66.

Chan, J., G. Koop, and S. Potter. 2016. "A Bounded Model of Time Variation in Trend Inflation, NAIRU and the Phillips Curve." *Journal of Applied Econometrics* 31 (3): 551–65.

Cogley, T., G. Primiceri, and T. Sargent. 2010. "Inflation-Gap Persistence in the US." *American Economic Journal: Macroeconomics* 2 (1): 43–69.

Galí, J. 2015a. "Hysteresis and the European Unemployment Problem Revisited." Paper presented at the ECB Forum on Central Banking, Sintra, Portugal, May 21–23.

———. 2015b. *Monetary Policy, Inflation and the Business Cycle: An Introduction to the New Keynesian Framework.* Second Edition. Princeton University Press.

Galí, J., F. Smets, and R. Wouters. 2012. "Unemployment in an Estimated New Keynesian Model." *NBER Macroeconomics Annual 2011*, ed. D. Acemoglu and M. Woodford, 329–60 (chapter 6). Chicago: University of Chicago Press.

Gillitzer, C., and J. Simon. 2015. "Inflation Targeting: A Victim of Its Own Success." *International Journal of Central Banking* 11 (Supplement 1): 259–87.

Gordon, R. J. 1998. "Foundations of the Goldilocks Economy: Supply Shocks and the Time-Varying NAIRU." *Brookings Papers on Economic Activity* 2: 297–333.

———. 2011. "The History of the Phillips Curve: Consensus and Bifurcation." *Economica* 78 (309): 10–50.

Kabundi, A., and E. Schaling. 2013. "Inflation and Inflation Expectations in South Africa: An Attempt at Explanation." *South African Journal of Economics* 81 (3): 346–55.

Kabundi, A., E. Schaling, and M. Some. 2015. "Monetary Policy and Heterogeneous Inflation Expectations in South Africa." *Economic Modelling* 45 (February): 109–11.

Kydland, F. E., and E. C. Prescott. 1977. "Rules Rather than Discretion: The Inconsistency of Optimal Plans." *Journal of Political Economy* 85 (3): 473–91.

Matheson, T., and E. Stavrev. 2013. "The Great Recession and the Inflation Puzzle." *Economics Letters* 120 (3): 468–72.

Phillips, A. W. 1958. "The Relation Between Unemployment and the Rate of Money Wage Rates in the United Kingdom, 1861–1957." *Economica* 25 (100): 283–99.

Samuelson, P. A., and R. M. Solow. 1960. "Analytical Aspects of Anti-Inflation Policy." *American Economic Review: Papers and Proceedings* 50 (2): 177–94.

Sargent, T. 1980. "Rational Expectations and the Reconstruction of Macroeconomics." *Quarterly Review* (Federal Reserve Bank of Minneapolis) 4 (3, Summer): 15–19.

Schaling, E., and M. Hoeberichts. 2010. "Why Speed Doesn't Kill: Learning to Believe in Disinflation." *De Economist* 158 (1): 23–42.

Stella, A., and J. Stock. 2013. "A State-Dependent Model for Inflation Forecasting." International Finance Discussion Paper No. 1062, Board of Governors of the Federal Reserve System.

Stock, J., and M. Watson. 2007. "Why Has U.S. Inflation Become Harder to Forecast?" *Journal of Money, Credit and Banking* 39 (s1): 3–33.

Viegi, N. 2015. "Labour Market and Monetary Policy in South Africa." SARB Working Paper No. 15/01.

Liquidity Risk and Collective Moral Hazard*

Diana Bonfim[a] and Moshe Kim[b]
[a]Banco de Portugal and Católica Lisbon School of Business and Economics
[b]University of Haifa

Banks individually optimize their liquidity risk management, often neglecting the externalities generated by their choices on the overall risk of the financial system. However, banks may have incentives to optimize their choices not strictly at the individual level, but engaging instead in collective risk-taking strategies. In this paper we look for evidence of such behaviors in the run-up to the global financial crisis. We find strong and robust evidence of peer effects in banks' liquidity risk management. This suggests that incentives for collective risk-taking play a role in banks' choices, thus calling for a macroprudential approach to liquidity regulation.

JEL Codes: G21, G28.

*We thank the editor, Rafael Repullo, two anonymous referees, Rui Albuquerque, Paolo Angelini, António Antunes, Frederico Belo, Jan Marc Berk, Sigbjorn Berg, Arnoud Boot, Rosa Borges, Christa Bouwman, Martin Brown, Max Bruche, Jin Cao, Geraldo Cerqueiro, Ilan Cooper, Lammertjan Dam, Eduardo Dávila, Hans Degryse, John Driscoll, Jan Willem Van Den End, Falko Fecht, José Fique, Ralph de Haas, Florian Heider, Michael Koetter, Thea Kloster, Jan Pieter Krahnen, Ana Cristina Leal, Iman van Lelyveld, Antoine Martin, Jean-Stéphane Mésonnier, Steven Ongena, Ettore Panetti, Wayne Passmore, Alberto Pozzolo, Isabel Proença, Lev Ratnovski, Francisca Rebelo, Hugo Reis, Nuno Ribeiro, Kasper Roszbach, Abdelaziz Rouabah, Martín Saldías, Javier Suarez, Razvan Vlahu, Wolf Wagner, and participants in seminars in the Deutsche Bundesbank and in the University of Groningen, in the EEA 2014, IBEFA 2014 Summer Meeting, Day Ahead Conference 2013 at the Bank of England, PET 2013 Conference, 5th Banco de Portugal Conference on Financial Intermediation, 2nd MoFiR Workshop on Banking, 6th CEPR Winter Conference on Financial Intermediation, 4th Financial Stability Conference in Tilburg, EBA Research Workshop on Banks' Business Models After the Crisis: Incentives, Strategies, De-risking, PFN2012, and CREDIT 2011 for insightful comments and suggestions. This paper was previously circulated with the title "Liquidity Risk in Banking: Is There Herding?". The analyses, opinions, and findings of this paper represent the views of the authors, which are not necessarily those of Banco de Portugal or the Eurosystem. Author e-mails: dbonfim@bportugal.pt and kim@econ.haifa.ac.il.

1. Introduction

Banks create liquidity in an economy, funding illiquid assets (such as loans) with liquid liabilities (such as deposits), as discussed by Berger and Bouwman (2009) and Bouwman (2014). This basic intermediation role of banks relies on a maturity mismatch between assets and liabilities, making them exposed to bank runs or, more generally, to funding liquidity risk. There is a vast and prominent theoretical literature on this problem. Bryant (1980) and Diamond and Dybvig (1983) provide the pillars for the analysis of banks' liquidity risk and bank runs, while other important contributions include Allen and Gale (2004a, 2004b), Calomiris and Kahn (1991), Diamond and Rajan (2000, 2001a, and 2001b), Klein (1971), Ratnovski (2009), and Wagner (2007a). However, there is surprisingly scarce empirical evidence on banks' maturity mismatches and funding liquidity risk.

In this paper, we contribute to fill this gap by empirically analyzing the way banks manage their liquidity risk. More specifically, we analyze the determinants of banks' liquidity risk management choices, explicitly considering potential strategic interactions among banks. This issue has important policy implications, as banks may have incentives to engage in collective risk-taking strategies when there is a strong belief that a (collective) bailout is possible (Acharya, Mehran, and Thakor 2016; Acharya and Yorulmazer 2007; Farhi and Tirole 2012). When other banks are taking more risk, a given bank may be encouraged to pursue similar strategies if its managers believe they will likely be rescued in case of distress. These collective risk-taking strategies may be optimal from an individual perspective, as they should allow banks to increase profitability without increasing the likelihood of bankruptcy, due to the explicit or implicit commitment of the lender of last resort. Hence, these risk-taking strategies may be mutually reinforcing in some circumstances. This collective behavior transforms a traditionally microprudential dimension of banking risk into a macroprudential risk, which may ultimately generate much larger costs to the economy.

However, it is important to note that the empirical estimation of these peer effects among banks raises some econometric challenges. As discussed by Manski (1993), the identification of endogenous and exogenous effects is undermined by the reflection problem associated with the reverse causality of peer effects. In other words, if we argue that peers' choices may affect the decisions of a specific bank, we cannot rule out that the decisions of that bank will not, in turn, affect the choices made by peers.

In our setting, the best solution available to this critical identification problem relies on the use of instrument variables, which have to be orthogonal to systematic or herding effects. Given the identification challenges associated with peer effects estimation (Angrist 2014), we rely on two main approaches. First, we use as an instrument for the peer effects the predicted values of liquidity indicators of peer banks based on regressions analyzing the determinants of liquidity indicators. In this setting, the predicted values depend on observable characteristics of the banks in the peer group. In other words, the predicted value of the liquidity indicators of peer banks should not directly affect the liquidity indicators of bank i at time t, as these predicted values are based solely on observable bank characteristics. By controlling also for country-year fixed effects, we are able to orthogonalize all country-specific time-varying shocks, such as changes in macroeconomic and financial conditions, as well as changes in the regulatory environment. Second, we consider the approach suggested by Leary and Roberts (2014). These authors identify the role of peer effects in corporate finance decisions using the idiosyncratic component of peer firms' equity returns. Given that this idiosyncratic component is entirely firm specific, it affects only the decisions of each firm individually, thereby satisfying the necessary exclusion restrictions for identification. However, this identification scheme allows us to consider only publicly listed banks, which account for less than 30 percent of the sample, being mostly U.S. banks (92 percent). In both approaches, the benchmark peer group is the banks operating in the same country in each year, as these are the banks that are more likely to share common beliefs about the likelihood of being bailed out by their common lender of last resort.

We obtain strong and consistent evidence of collective risk-taking behaviors in liquidity risk management. We are aware that to perfectly estimate the magnitude of peer effects we would need a fully experimental setting, which is not available when studying banks' behavior. Thus, to further minimize the perils of peer effects estimation (Angrist 2014), we run exhaustive robustness tests, including the use of alternative identification strategies and other peer group definitions. Our main results remain valid, supporting the existence of significant peer effects between banks in their liquidity risk management strategies.

Having established the existence of peer effects, it is important to dig deeper and understand where these strategic interactions are coming from. Are peer effects stronger for some groups of banks? Are there leaders and followers in this strategic game? We find that collective risk-taking strategies are much weaker for small banks, as well as for the very large banks. The core of strategic interactions in liquidity risk management is concentrated in large banks that are just below the threshold of being too big to fail. These results are entirely consistent with the theoretical predictions of Farhi and Tirole (2012) and Ratnovski (2009). Smaller banks will hardly ever be bailed out. In contrast, the largest banks expect to be bailed out in almost any circumstance. However, large banks just below this threshold might expect to be bailed out if the stability of the whole financial system or the economy is at stake. This would be the case if systemic risk and contagion fears are heightened. By correlating their decisions and adopting collective risk-taking strategies, these banks thus increase the likelihood of being bailed out.

Our results have valuable policy implications: liquidity risk is usually regulated from a microprudential perspective, but our results show that a macroprudential approach to the regulation of systemic liquidity risk should not be disregarded. Given this, even though the new Basel III package on liquidity risk is a huge step forward in the regulation of liquidity risk, additional macroprudential policy tools may need to be considered, as the new regulation is still dominantly microprudential. For instance, macroprudential authorities may consider imposing tighter liquidity regulation or limits to certain types of exposure, in order to mitigate contagion and systemic risks, thereby providing the correct incentives to minimize negative externalities.

The contribution of our paper is manyfold. Even though the theoretical literature provides many relevant insights and testable hypotheses regarding banks' liquidity risk, there is scarce empirical evidence on banks' liquidity risk management. Furthermore, we focus on a period of particular importance, as there is an extensive discussion regarding excessive risk-taking in the years preceding the global financial crisis. We provide detailed empirical evidence on the determinants of liquidity risk, and more importantly, we extend the analysis by focusing on strategic interactions. Further, we make an effort to provide a correct and rigorous econometric treatment for the endogeneity of peer effects in a multivariate setting. Finally, our results provide important insights for policymakers, most notably regarding the macroprudential regulation of systemic liquidity risk.

This paper is organized as follows. We begin by reviewing the expanding literature on bank's funding liquidity risk and its regulation, in section 2. In section 3 we discuss several indicators of banks' liquidity risk and characterize the data set used for the empirical analysis, including an overview of banks' liquidity and funding choices in the run-up to the recent global financial crisis. In section 4 we analyze how banks manage their liquidity risk, and in section 5 we address the most important question in our paper: do banks take into account peers' liquidity strategies when making their own choices on liquidity risk management? In section 6 we summarize our main findings and discuss their policy implications.

2. Related Literature

In recent years banks have become increasingly complex institutions through their exposure to an intertwined set of risks. Traditionally, most bank loans would be funded with customer deposits. These liquid claims allow consumers to intertemporally optimize their consumption preferences, but leave banks exposed to the risk of bank runs, as shown by Diamond and Dybvig (1983). Over time, banks gained access to a more diversified set of liabilities to fund their lending activities (Strahan 2008), thus being exposed not only to traditional runs from depositors but also to the drying up of funds in wholesale markets, as discussed by Borio (2010) and Huang and Ratnovski (2011).

The 2008 global financial crisis placed liquidity risk in the spotlight and made it clear that something was missing in the international regulatory consensus (Bouwman 2014, Vives 2014). While banks voluntarily hold buffers of liquid assets to manage the risks associated with the maturity gap between assets and liabilities (Acharya, Mehran, and Thakor 2016; Acharya, Shin, and Yorulmazer 2011; Allen and Gale 2004a, 2004b; Bouwman 2014; Calomiris, Heider, and Hoerova 2013; Farhi, Golosov, and Tsyvinski 2009; Feinman 1993; Gale and Yorulmazer 2013; Rochet and Vives

2004; Tirole 2011; and Vives 2014), these buffers will hardly ever be sufficient to fully insure against a bank run or a sudden dry-up in wholesale markets.

Allen and Gale (2004a, 2004b) show that liquidity risk regulation is necessary when financial markets are incomplete, though emphasizing that all interventions inevitably create distortions. Furthermore, Rochet (2004) argues that banks take excessive risk if they anticipate that there is a high likelihood of being bailed out in case of distress. Regulation may mitigate this behavior (Acharya, Shin, and Yorulmazer 2011; Brunnermeier et al. 2009; Cao and Illing 2010; Gale and Yorulmazer 2013; Holmstrom and Tirole 1998; and Tirole 2011).[1]

When regulation fails to preemptively address risks, the intervention of the lender of last resort might be necessary. However, the lender of last resort has an intrinsic moral hazard problem (see, for example, Freixas, Parigi, and Rochet 2004, Gorton and Huang 2004, Ratnovski 2009, Rochet and Tirole 1996, Rochet and Vives 2004, and Wagner 2007a). This mechanism has to be credible ex ante to prevent crises. But if the mechanism is in fact credible, banks will know they will be helped out if they face severe difficulties, thus having perverse incentives to engage in excessive risk-taking behaviors (Ratnovski 2009). Repullo (2005) shows that the existence of a lender of last resort does not lead to risk-taking in banks' illiquid portfolios (i.e., their lending activities), but it reduces banks' incentives to hold liquid assets, thereby aggravating liquidity risk.

The moral hazard problem associated with the existence of a safety net provided by a lender of last resort is further aggravated

[1] Many authors discuss the importance of imposing minimum holdings of liquid assets (Acharya, Shin, and Yorulmazer 2011; Allen and Gale 2004a, 2004b; Farhi, Golosov, and Tsyvinski 2009; Gale and Yorulmazer 2013; Ratnovski 2009, 2013; Rochet and Vives 2004; Santos and Suarez 2018; Tirole 2011; and Vives 2014). However, Wagner (2007b) shows that, paradoxically, holding more liquid assets may induce more risk-taking by banks. Freixas, Martin, and Skeie (2011) show that central banks can manage interest rates to induce banks to hold liquid assets, i.e., monetary policy can help to promote financial stability. In turn, Bengui (2010) finds arguments to support a tax on short-term debt, whereas Cao and Illing (2011) show that imposing minimum liquidity standards for banks ex ante is a crucial requirement for sensible lender of last resort policies. Finally, Diamond and Rajan (2005) and Wagner (2007a) focus on ex post interventions.

by systemic behavior.[2] Indeed, when most banks are taking excessive risks, each bank manager has clear incentives to herd, instead of leaning against the wind. Ratnovski (2009) argues that, in equilibrium, banks have incentives to herd in risk management, choosing sub-optimal liquidity as long as other banks are expected to do the same. These collective risk-taking strategies may be optimal from an individual perspective, as they should allow banks to increase profitability without increasing the likelihood of bankruptcy, due to the explicit or implicit bailout commitment of the lender of last resort. Ratnovski (2009) thus identifies strategic complementarities between banks in their liquidity risk decisions. Banks will choose to be more exposed to liquidity risk when other banks do so, as this increases the likelihood of a systemic liquidity crisis and an ensuing bailout. Comparative statistics derived from the model show that this is more likely to happen when banks have lower charter values or expect shocks that may decrease that value, such as in the run-up to a crisis.

Some of these arguments are discussed in detail by Farhi and Tirole (2012), who argue that when banks simultaneously increase their liquidity risk, through larger maturity mismatches, current and future social costs are being created. In the presence of strategic complementarities between banks' maturity transformation decisions, central banks are forced to intervene as lenders of last resort. This not only creates social costs at the moment of intervention but also helps to change beliefs and sows the seeds for the next crisis. Given all these market failures, regulation is needed to ensure that these externalities are considered by banks in their liquidity risk management. In their model, optimal regulation is associated with the imposition of a liquidity requirement or an equivalent limit on short-term debt. Nevertheless, the costs and distortions generated by such regulation also need to be taken into account. The model suggests that regulation should be applied only to a subset of key institutions, which would be more likely to be bailed out.

[2]Citigroup's former CEO, Charles Prince, has been repeatedly quoted as saying before August 2007 that "When the music stops, in terms of liquidity, things will be complicated. But as long as the music is playing, you've got to get up and dance. We're still dancing."

However, the market failure behind regulation is not linked to a too-big-to-fail problem, but rather to a too-correlated-to-fail problem, as banks adopt excessive maturity mismatches together with correlated risks.

Acharya, Mehran, and Thakor (2015) and Acharya and Yorulmazer (2007) also discuss bailouts when there are many potentially correlated failures. Acharya, Shin, and Yorulmazer (2011) consider the effect of the business cycle on banks' optimal liquidity choices and prove that during upturns banks' choice of liquid assets jointly decreases. In turn, Allen, Babus, and Carletti (2012) show that when banks make similar portfolio decisions, systemic risk increases, as defaults become more correlated. Jain and Gupta (1987) find (weak) evidence on bank herding during a crisis period. Brown and Dinç (2011) provide evidence that governments are more likely to bail out a bank when the whole banking system is in distress, using a sample of banks from twenty-one emerging markets in the 1990s. Perotti and Suarez (2002) prove the existence of strategic interactions between banks, though their results support the existence of strategic substitutions rather than strategic complementarities. They show that if banks expect to obtain larger rents if their competitors fail, their speculative lending decisions are strategic substitutes. Collective risk-taking incentives and strategic complementarities are also discussed by Acharya (2009), Acharya and Yorulmazer (2008), Barron and Valev (2000), Boot (2011), Malherbe (2014), Rajan (2006), Tirole (2011), van den End and Tabbae (2012), and Vives (2014).

This emerging evidence on systemic liquidity risk calls for adequate macroprudential instruments that address the sources of such risks, as discussed by Boot (2011), Cao and Illing (2010), and Farhi and Tirole (2012). Nevertheless, most of these conclusions are supported by theoretical results, lacking empirical support. Our paper helps to fill this gap in the literature, by providing empirical evidence of collective risk-taking in liquidity risk management, anchored essentially on the theoretical findings of Farhi and Tirole (2012) and Ratnovski (2009) on strategic complementarities.

Silva (2017) also documents peer effects in liquidity risk, though our papers differ in several dimensions. While Silva (2017) makes an effort to understand if the estimated peer effects have effects on overall financial stability, we focus on understanding where these peer effects come from, by exploring interactions between different groups of banks.[3]

3. How to Measure Liquidity Risk?

The maturity transformation role of banks generates funding liquidity risk (Diamond and Dybvig 1983). As banks' liabilities usually have shorter maturities than those of banks' assets, banks have to repeatedly refinance their assets. In the run-up to the global financial crisis, many banks were engaging in funding strategies that relied heavily on short-term funding (Brunnermeier 2009; Committee on the Global Financial System 2010), thereby significantly increasing their exposure to funding liquidity risk.

In this section we describe the data used and briefly review several ways to measure funding liquidity risk, which will later be used in our empirical analysis.

3.1 Data

Given that one of our objectives is to assess the extent to which banks take each others' choices into account when managing liquidity risk, we must consider a sufficiently heterogeneous group of banks. With that in mind, we collect data from Bankscope for the period between 2002 and 2009, thus covering both crisis and pre-crisis years. We collect data on European and North American banks, selecting only commercial banks and bank holding companies for which consolidated statements are available in universal

[3]There are at least two other important differences between the papers. First, we consider that peer effects are mainly driven by common beliefs about the possible intervention of a lender of last resort (Ratnovski 2009). As such, we consider that our empirical strategy to deal with the estimation of peer effects is more adequate for the purpose of our study than that used in Silva (2017), in which a foreign parent bank holding group influences the decisions of its domestic subsidiary, thus generating partially overlapping peer groups. Second, Silva (2017) uses data up to 2014, while our analysis is based on data up to only 2009. We believe that extending the sample for the 2010–14 period might bias the estimation of peer effects, as the Basel Committee issued its first guidelines on the new liquidity regulation that would be part of Basel III in 2010 (Basel Committee on Banking Supervision 2010). We should thus expect that banks began to change their liquidity ratios in the same direction simultaneously in reaction to the new Basel rules, which could lead to an over-estimation of peer effects.

Table 1. Banks' Characteristics

	N	Mean	Min.	P25	P50	P75	Max.
Total Assets	17,620	21,200	92	295	659	2,183	772,000
Total Capital Ratio	10,211	14.5	7.3	11.3	12.9	15.6	44.5
Tier 1 Ratio	9,851	12.6	4.7	9.5	11.2	13.9	41.6
Net Interest Margin	17,561	3.7	0.3	3.0	3.8	4.4	10.4
Return on Assets	17,596	0.9	−4.9	0.5	1.0	1.3	5.1
Cost to Income	17,510	67.1	27.4	56.7	65.0	74.2	165.1
Net Loans to Total Assets	17,509	63.0	5.1	55.1	66.4	75.2	90.6

Notes: Total assets are in millions of USD. The total capital and tier 1 ratios are calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets is computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks' operational costs (overheads) as a percentage of income generated before provisions. These variables are included in the Bankscope database. The statistics presented refer to data after outliers were winsorized.

format, so as to ensure the comparability of variables across countries. Savings and investment banks are not included in the data set, as they usually have different liquidity risk profiles and funding strategies. Using these filters, we obtain data for almost 3,500 banks during eight years, for forty-five countries.[4] Excluding banks without information on total assets, we obtain 17,643 bank-year observations.

In table 1 we summarize the major characteristics of the banks included in the sample.

3.2 Liquidity Indicators

In table 2 we present summary statistics on liquidity risk for the banks included in the sample. As discussed by Tirole (2011),

[4]These countries are Albania, Andorra, Austria, Belarus, Belgium, Bosnia-Herzegovina, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Moldova Republic, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russian Federation, San Marino, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom, and United States. In Albania, Bosnia-Herzegovina, Liechtenstein, Moldova Republic, Montenegro, and San Marino there are fewer than ten observations for the entire sample period. Given this, we exclude these six countries from all cross-country analysis.

Table 2. Liquidity Indicators: Summary Statistics

A. Global Summary Statistics									
	N	**Mean**	**Min.**	**P25**	**P50**	**P75**	**Max.**		
Liquidity Creation	17,620	9.1	−35.7	−4.8	4.8	22.1	69.2		
NSFR	17,618	115.1	27.8	106.7	121.2	129.9	155.1		
B. Liquidity Indicators Over Time (Mean)									
	2002	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**Total**
Liquidity Creation	2.7	2.5	3.8	6.9	13.0	13.7	13.9	24.9	9.1
NSFR	122.2	122.6	119.9	116.9	109.4	108.5	108.2	104.5	115.1

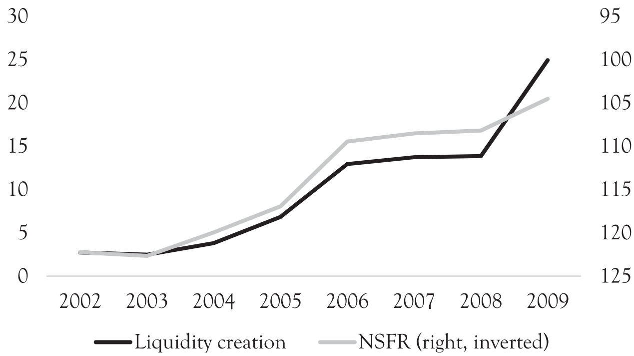
Notes: Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the net stable funding ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assets that need to be funded). These two variables are negatively correlated (i.e., more liquidity risk is associated with higher liquidity creation and lower NSFR) and are defined in detail in the data appendix. The statistics presented refer to data after outliers were winsorized.

liquidity cannot be measured by relying on a single variable or ratio, given its complexity and the multitude of potential risk sources. Ideally, a complete liquidity indicator would rely on the overall liquidity mismatch between assets and liabilities. However, the data necessary for such an indicator is usually not publicly available. Nevertheless, some approximation is feasible. Taking that into account, we focus our analysis on two indicators that offer an encompassing view of banks' liquidity risk: (i) *liquidity creation* and (ii) *net stable funding ratio.*

Liquidity creation as a percentage of total assets is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). These authors define liquidity creation as

$$\begin{aligned} &Liquidity\_creation \\ &\quad = \{1/2 * Illiq\_assets + 0 * Semi\_liq\_assets - 1/2 * Liq\_assets\} \\ &\qquad + \{1/2 * Liq\_liabilities + 0 * Semi\_liq\_liab. - 1/2 * Illiq\_liab.\} \\ &\qquad - 1/2 * Capital. \end{aligned}$$

Figure 1. Liquidity Indicators Over Time (Mean)



The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. More liquidity is created when illiquid assets are transformed into liquid liabilities. Of course, liquidity creation is positively related with funding liquidity risk, given that banks that create more liquidity have fewer liquid assets to meet short-term funding pressures.[5]

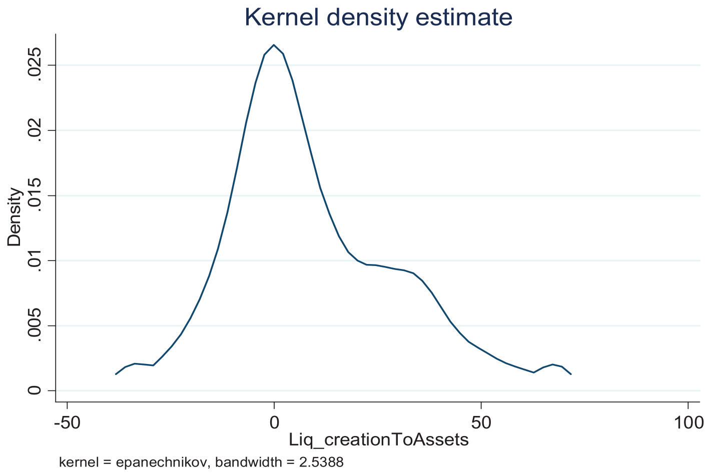
Liquidity creation increased steadily during the sample period, including during the crisis years (figure 1). Actually, its highest value was recorded in 2009, thus showing that banks continued to create liquidity even during the global financial crisis. However, this also implies that liquidity risk increased during this period, according to this indicator. However, it is important to note that this indicator continued to increase during the crisis because banks' total assets contracted more than liquidity creation itself.

Figure 2 shows that this variable exhibits some dispersion during our sample period.

In turn, the net stable funding ratio (NSFR) included in the Basel III package is a structural ratio designed to address liquidity

[5]Berger and Bouwman (2009) consider two different measures of liquidity creation. Besides the one presented above, there is another definition that considers off-balance-sheet data. Though the latter definition is more encompassing, capturing better the liquidity created by a bank, the data available in Bankscope do not allow us to compute it for our sample. Please see the data appendix for further details.

Figure 2. Empirical Distribution of the Liquidity Creation Ratio



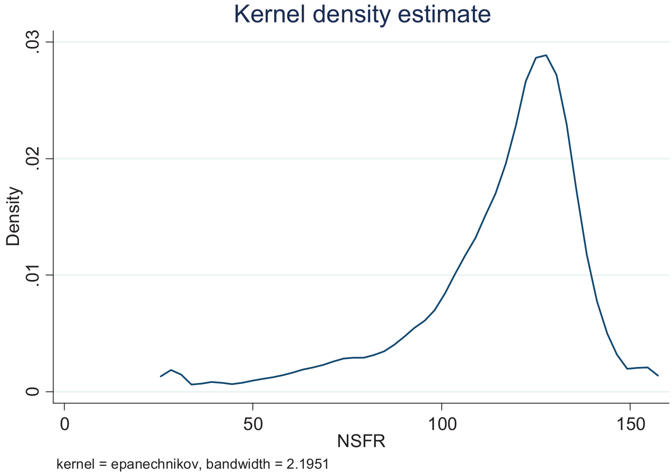
Notes: Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. See the data appendix for further details.

mismatches and to encourage an increased reliance on medium- and long-term funding, thus increasing the average maturity of banks' liabilities. The NSFR is the ratio between the available and the required amount of stable funding, which should be at least 100 percent. The higher this ratio is, the more comfortable is the institution's liquidity position. Though the available data do not allow for the accurate computation of this indicator, a rough approximation is possible.[6]

The NSFR showed some deterioration in the run-up to the crisis. Figure 3 shows that most banks record high values in this ratio. It is important to stress that this indicator is an approximation of the indicator proposed by the Basel Committee. As such, the 100 percent minimum threshold defined for this ratio for prudential purposes cannot be considered for our indicator.

[6]Please see the data appendix for further details.

Figure 3. Empirical Distribution of the NSFR



Notes: NSFR is an approximation of the net stable funding ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assets that need to be funded). See the data appendix for further details.

The two liquidity indicators used in our analysis offer an encompassing view of banks' liquidity risk because they contain information from all assets and liabilities.

Our main research question is to understand if collective strategies played a role in these developments. But before we address this question, in the next section we will provide some insight on which factors are relevant to explain the heterogeneity in liquidity indicators. This analysis is relevant given the lack of empirical evidence on the determinants of liquidity risk. Only after having clarified that will we be able to understand how peer effects work over and above the individual determinants of liquidity indicators.

4. How Do Banks Manage Liquidity Risk?

Even though liquidity risk management is one of the most important decisions in the prudent management of financial institutions, there is scarce empirical evidence on the determinants of liquidity indicators. Using our data set, we are able to explore which bank characteristics may be relevant in explaining liquidity indicators. In table 3 we present some results on the two main liquidity indicators described in the previous section: (i) liquidity creation (column 1); and (ii) net stable funding ratio (column 2). All specifications use robust standard errors, bank fixed effects, and country-year fixed effects, such that

$$\begin{aligned} Liqx_{it} = {} & \alpha_0 + \alpha_i + \alpha_{nt} + \beta_1 Capital_{it-1} + \beta_2 Banksize_{it} \\ & + \beta_3 Profitability_{it-1} + \beta_4 Cost\_inc_{it-1} \\ & + \beta_5 Lend\_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t + \varepsilon_{it}, \end{aligned} \tag{1}$$

where $Liqx_{it}$ is the liquidity indicator analyzed, α_0 is a constant, α_i is the bank fixed effect, α_{nt} is the country-year fixed effect, i_t is the year fixed effect, and ε_{it} is the estimation residual. Bank fixed effects allow us to control for all time-invariant bank characteristics, while country-year fixed effects control for all country-specific time-varying shocks, such as changes in macroeconomic and financial conditions, or changes in the regulatory environment. By controlling also for time fixed effects, we are able to orthogonalize all systematic and common shocks to banks.

As explanatory variables, we use a set of core bank indicators on solvency, size, profitability, efficiency, and specialization. $Capital_{it}$ is the total capital ratio calculated according to the rules defined by the Basel Committee. Pierret (2015) shows that there are important interactions between liquidity risk and banks' solvency. Banks face higher refinancing risk if markets question their solvency in a crisis. Based on this, we could expect that banks with lower capital ratios have more prudent liquidity risk management policies. Indeed, de Haan and van den End (2013) find that there is a negative relationship between capital ratios and liquidity buffers of Dutch banks. However, Bonner, van Lelyveld, and Zymek (2015) and Dinger (2009) obtain the opposite result using data from banks in multiple countries. This might reflect the fact that some banks engage in overall more prudent risk management strategies, holding larger capital and liquidity buffers, while others do the opposite.

Table 3. Determinants of Liquidity Indicators

Dependent Variable →	**Liquidity Creation**	**NSFR**
	(1)	**(2)**
Total Capital Ratio$_{t-1}$	−0.14	0.07
	(−1.56)	(0.85)
Log Assets$_t$	−5.87***	−2.69**
	(−4.96)	(−2.46)
Net Interest Margin$_{t-1}$	−1.37***	2.11***
	(−3.96)	(5.95)
Return on Assets$_{t-1}$	0.68*	−1.43***
	(1.81)	(−3.66)
Cost-to-Income$_{t-1}$	0.08***	−0.04**
	(3.72)	(−2.10)
Net Loans to Total Assets$_{t-1}$	0.29***	0.11**
	(6.72)	(2.03)
Loans to Customer Deposits$_{t-1}$	−0.02**	−0.08***
	(−2.01)	(−5.77)
Liquidity Ratio$_{t-1}$	0.23***	0.04
	(7.90)	(1.36)
Liquidity Creation$_{t-1}$	—	−0.14***
	—	(−4.22)
NSFR$_{t-1}$	−0.15***	—
	(−5.31)	—
D2004	−3.74***	2.10***
	(−10.36)	(5.36)
D2005	−3.66***	1.13**
	(−8.58)	(2.55)
D2006	−7.35***	4.49***
	(−21.51)	(11.57)
D2007	−9.08***	4.79***
	(−23.22)	(12.18)
D2008	−11.59***	5.08***
	(−27.44)	(13.43)
Constant	−593.2***	355.24***
	(−15.33)	(9.92)
Number of Observations	7,020	7,020
Number of Banks	1,738	1,738
R2 Within	0.366	0.160
R2 Between	0.139	0.165
R2 Overall	0.103	0.138
Fraction of Variance Due to Bank FE	0.998	0.984

Notes: All regressions include country-year fixed effects, bank fixed effects, and robust standard errors. t-statistics are in parentheses. The total capital ratio is calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets is computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks' operational costs (overheads) as a percentage of income generated before provisions. Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the net stable funding ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assets that need to be funded). These two variables are negatively correlated (i.e., more liquidity risk is associated with higher liquidity creation and lower NSFR) and are defined in detail in the data appendix. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level, respectively.

$Banksize_{it}$ is measured by the log of assets. Larger banks might show poorer liquidity indicators for two reasons. First, larger banks can more easily have access to markets and might thus afford to hold less liquid assets. Second, larger banks are often perceived as too big to fail, thus having fewer incentives to have very prudent (and costlier) liquidity risk management strategies. Indeed, Dinger (2009) and Kashyap, Rajan, and Stein (2002) find that larger banks hold fewer liquid assets, though Aspachs, Nier, and Tisset (2005) find no significant effects for U.K. banks.

$Profitability_{it}$ is proxied by the return on assets and the net interest margin. On the one hand, more-profitable banks may allocate part of their cash flows to holdings of liquid assets. On the other hand, these banks may be confident in their ability to continue to generate cash flows, thus holding fewer liquidity buffers. Indeed, the results in the literature are mixed. Bonner, van Lelyveld, and Zymek (2015) find that there is a positive relationship between profitability and liquidity holdings, while Deléchat et al. (2012) find a negative effect, and Aspachs, Nier, and Tisset (2005) do not find significant effects.

$Cost\_inc_{it}$ refers to the cost-to-income ratio, which is a proxy for cost-efficiency. Banks' liquidity risk management policies might also be related with their operational efficiency. However, as for profitability, the sign of this relationship is uncertain.

Finally, $lend\_spec_{it}$ measures the extent to which a bank is specialized in lending, by considering net loans as a percentage of total assets. We include this variable to control for banks' business models. Banks that are specialized in lending have a more traditional intermediation profile. This may mean that they also have more conservative risk management practices. Alternatively, given that loans are an illiquid asset, they may hold proportionally fewer liquid assets than a more diversified bank.

$(Liq - x_{it})$ refers to the other liquidity indicators, i.e., $x_{it} \neq -x_{it}$. Given that liquidity risk is hard to capture using one single indicator, as discussed above, we consider that it is important to control for the other liquidity indicators, as they jointly characterize the risk profile of each institution.

All variables are lagged by one period to mitigate concerns of simultaneity and reverse causality.

Even though some relationship between capital and liquidity could be expected (Berger and Bouwman 2009, Diamond and Rajan 2000, 2001b), the total capital ratio is not statistically significant in any of the specifications tested.

The results on bank size are mixed. While larger banks create less liquidity (column 1), thereby showing less liquidity risk, they have lower NSFRs (column 2), thus being riskier in this dimension.

The relationship between profitability and liquidity risk is rather mixed. On the one hand, when banks obtain larger net interest margins, they seem to display lower liquidity risk, when measured both by liquidity creation and NSFR. On the other hand, when banks record higher overall profitability, as measured by return on assets, they show more liquidity risk (more liquidity creation and less-stable funding structures). Banks that are more profitable in their basic intermediation function seem to have less risky funding structures, while banks that are broadly more profitable (possibly obtaining larger gains from other income sources) tend to be riskier in their liquidity risk management. These are possibly banks that adopt riskier strategies in order to boost profitability, thus being more vulnerable to funding liquidity risk. This result is in line with Demirgüç-Kunt and Huizinga (2010), who show that banks that rely on strategies based on non-interest income and on short-term funding are significantly riskier.

In turn, when banks become more efficient, with lower cost-to-income ratios, they create, on average, less liquidity and have larger net stable funding ratios.

The relationship between liquidity risk and bank specialization is different depending on the liquidity indicator used. On the one hand, banks that become more specialized in lending to customers tend to create more liquidity. On the other hand, these banks show more stable funding structures.

Finally, it is worth noting that much of the variation in liquidity ratios cannot be attributable to the observed financial ratios. Indeed, as shown in table 3, bank fixed effects account for a very large fraction of the variance. This result is entirely consistent with evidence obtained by Gropp and Heider (2010) regarding the determinants of banks' capital ratios. These authors find that unobserved time-invariant bank fixed effects are ultimately the most important determinant of banks' capital ratios.

5. Are Other Banks' Decisions Relevant?

In the previous section we shed some light on the role of different bank characteristics in their observed liquidity strategies. However, it is possible to argue that banks do not optimize their liquidity choices strictly individually and may take into account other banks' choices. In fact, when banks believe that they may be bailed out in case of severe financial distress (for being too big, too systemic, or too interconnected to fail), they may actually have incentives to herd, engaging in similar risk-taking and management strategies.

In this section we seek evidence of possible herding behavior of banks in liquidity risk management, especially in the years before the global financial crisis. The identification and measurement of peer effects on individual choices is a challenging econometric problem, as discussed by Manski (1993). In section 5.1 we briefly discuss these identification problems, in section 5.2 we propose an empirical strategy to address these concerns, and in section 5.3 we present our main results. To mitigate the perils of peer effect estimation (Angrist 2014), we perform an extensive robustness analysis including using alternative identification strategies and running estimations for subsets of countries, banks, and time periods. We also consider other peer group definitions, as this issue is critical for identification. For instance, we consider the role of strategic interactions between large and small banks, and also test whether small banks follow the strategies of large banks.

5.1 The Reflection Problem and Identification Strategies

In a multivariate setting, the impact of peers' liquidity indicators on a bank's liquidity decisions could be estimated through the following adapted version of equation (1):

$$\begin{aligned} Liqx_{it} = {} & \alpha_0 + \alpha_i + \alpha_{nt} + \beta_0 \sum_{j \neq i} \frac{Liqx_{jt}}{N_{it} - 1} + \beta_1 Capital_{it-1} \\ & + \beta_2 Banksize_{it} + \beta_3 Profitability_{it-1} + \beta_4 Cost\_inc_{it-1} \\ & + \beta_5 Lend\_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t + \varepsilon_{it}, \qquad (2) \end{aligned}$$

where $\sum_{j \neq i} \frac{Liqx_{jt}}{N_{it}-1}$ represents the average liquidity indicators of peers and all the other variables and parameters are defined as in equation (1). In the baseline specification, the peer banks are all the other banks operating in the same country, which share common beliefs about the lender of last resort. The coefficient β_0 captures the extent to which banks' liquidity choices reflect those of the peer group. Recall that we are controlling for bank, time, and country-year fixed effects.

However, this estimation entails some econometric problems: as we argue that peer choices may affect the decisions of a specific bank, we cannot rule out that the decisions of that bank will not, in turn, affect the choices made by peers. This reverse causality problem in peer effects is usually referred to as the reflection problem. This problem was initially described by Manski (1993), who distinguishes three different dimensions of peer effects: (i) endogenous effects, (ii) exogenous or contextual effects, and (iii) correlated effects. Endogenous effects arise from the influence of peer outcomes and are what we usually think of as "pure" peer effects. In our case, this is directly related to observed liquidity decisions. Banks choose their liquidity risk management strategies taking into account the choices made by other banks. Exogenous or contextual effects are related with the influence of exogenous peer characteristics. For instance, if other banks are making higher profits, bank i may engage in risk-taking strategies to increase its profitability. This may be achieved by assuming less prudent liquidity risk management strategies. In this case, the peer effect is not so directly linked to the outcome variable. When we control for banks' time-varying characteristics we try to mitigate this concern. Finally, there are correlated effects, which affect all elements of a peer group simultaneously. For instance, changes in monetary policy, macroeconomic conditions, or bailout expectations may lead to simultaneous changes in banks' liquidity strategies. We are able to control these using time fixed effects and country-year fixed effects.

Empirically, it is very challenging to disentangle these three effects. More specifically, Manski (1993) discusses the difficulties arising from the distinction between effective peer effects (either endogenous or exogenous) from other correlated effects. Furthermore, the identification of endogenous and exogenous effects is undermined by this reflection problem, as the simultaneity in peers' decisions should result in a perfect collinearity between the expected mean outcome of the group and its mean characteristics, as discussed also by Bramoullé, Djebbari, and Fortin (2009) and Carrell, Fullerton, and West (2009).

This discussion makes clear that the estimation of equation (2) may not allow for the accurate estimation of peer effects. Our solution to this important identification problem relies on the use of instrumental variables to address this endogeneity problem. Manski (2000) argues that the reflection problem can be solved if there is an instrumental variable that directly affects the outcomes of some, but not all, members of the peer group.[7] As discussed in Brown et al. (2008) and Leary and Roberts (2014), such an instrument must be orthogonal to systematic or herding effects. We considered two different approaches.

First, we use as instruments the predicted values of liquidity indicators of peer banks based on the regressions of the determinants of liquidity indicators presented in table 3. The predicted values depend on the characteristics of the banks in the peer group, excluding bank i. To ensure that the instrument is valid, the predicted values of peer banks should be highly correlated with the average of the observed liquidity indicators, our potentially endogenous variable. More importantly, for the exclusion restriction to hold, the predicted values should be orthogonal to systematic or herding effects. In other words, the predicted value of the liquidity indicators of peer banks should not directly affect $Liqx_{it}$, the liquidity indicator of bank i at time t, as these predicted values are based solely on observable bank characteristics.

Given that the instrumental variable is a linear combination of observed bank characteristics, we believe that the exclusion restriction holds. The coefficients sustaining this linear combination come from a regression in which we explore the role of bank characteristics in explaining liquidity ratios. A bank with a given amount of

[7]Other solutions to the reflection problem found in the literature are, for example, having randomly assigned peer groups (Sacerdote 2001), having variations in group sizes (Lee 2007), or identifying social networks using spatial econometrics techniques (Bramoullé, Djebbari, and Fortin 2009). Given the characteristics of peer groups in our sample, none of these solutions can be applied in our setting.

capital, with a given return on assets, etc., is expected to have a certain liquidity ratio. This should not be contaminated by the effect of peer choices.

Importantly, as we control also for time effects, we are able to orthogonalize all systematic shocks to banks. In addition, we control for country-year fixed effects, in order to consider the effect of time-varying country characteristics that may simultaneously affect all banks in a given country. As such, the estimated peer effects are orthogonal to time-varying common factors that affect all banks in each country.

Formally, our instrumental-variables approach is equivalent to the estimation of

$$\begin{aligned} Liqx_{it} = {} & \alpha_0 + \alpha_i + \alpha_{nt} + \beta_0 \sum_{j \neq i} \frac{Liqx_{jt}}{N_{it} - 1} + \beta_1 Capital_{it-1} \\ & + \beta_2 Banksize_{it} + \beta_3 Profitability_{it-1} + \beta_4 Cost\_inc_{it-1} \\ & + \beta_5 Lend\_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t + \varepsilon_{it}. \end{aligned} \tag{3}$$

The peer effects, $\sum_{j \neq i} \frac{Liqx_{jt}}{N_{it}-1}$, i.e., the average liquidity indicators of peers, are instrumented by the predicted values of liquidity ratios for these peers $\left(\sum_{j \neq i} \frac{Liq\_predx_{jt}}{N_{it}-1} \right)$, as shown in the first-step equation:

$$\begin{aligned} \beta_0 \sum_{j \neq i} \frac{Liqx_{jt}}{N_{it} - 1} = {} & \alpha_0 + \alpha_j + \alpha_{nt} + \gamma_1 \sum_{j \neq i} \frac{Liq\_predx_{jt}}{N_{it} - 1} \\ & + \beta_1 Capital_{jt-1} + \beta_2 Banksize_{jt} \\ & + \beta_3 Profitability_{jt-1} + \beta_4 Cost\_inc_{jt-1} \\ & + \beta_5 Lend\_spec_{jt-1} + \beta_6 (Liq - x_{jt-1}) + i_t + \varepsilon_{it}. \end{aligned} \tag{4}$$

The predicted values Liq_predx_{jt} are obtained from a bank-level equation in which we consider the entire set of bank characteristics:

$$\begin{aligned} Liq\_predx_{it} = {} & \alpha_0 + \alpha_i + \alpha_{nt} + \beta_1 Capital_{it-1} + \beta_2 Banksize_{it} \\ & + \beta_3 Profitability_{it-1} + \beta_4 Cost\_inc_{it-1} \\ & + \beta_5 Lend\_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t. \end{aligned} \tag{5}$$

Second, we consider an entirely different instrument based on the empirical strategy followed by Leary and Roberts (2014). To identify peer effects in corporate financial policy, these authors looked for an instrument that would not directly affect the financing decisions of a given firm, but that would influence those of the peer group of firms. An instrument that fulfills these exclusion and relevance conditions is the idiosyncratic component of peer firms' equity returns. We follow a similar approach, by computing bank-specific equity returns as the difference between the bank's returns and those of the S&P banks index in a given year.[8]

As before, we define the benchmark peer group as the banks operating in the same country and in the same year. These are the banks that are more likely to engage in collective risk-taking behaviors due to implicit or explicit bailout expectations. Let us suppose that in a given country several banks engage in funding liquidity strategies that are deemed as overall risky (e.g., excessive reliance on short-term debt to finance long-term assets, large funding gaps, or persistent tapping of interbank markets). If several banks engage

[8]This approach is simpler than that used by Leary and Roberts (2014), who estimate idiosyncratic returns using an augmented factor model such that

$$R_{ijt} = \alpha_{ijt} + \beta_{ijt}^{M}(RM_t - RF_t) + \beta_{ijt}^{SMB}(SMB_t) + \beta_{ijt}^{HML}(HML_t) + \beta_{ijt}^{MOM}(MOM_t) + \beta_{ijt}^{IND}(R_{jt} - RF_t) + \eta_{ijt},$$

where R_{ijt} refers to the total return for firm i in industry j over month t. The first four factors are those commonly used in empirical asset pricing studies (Fama and French 1993). The fifth factor is the excess return on an equally weighted industry portfolio. This augmented model is justified by the fact that in their paper peer effects are being estimated at the industry level, while our paper focuses on only the banking sector. We simplified our approach even further for two main reasons. First, in these regressions we are dealing with a relatively small number of banks (around 400), thus raising issues about the definitions of the small minus big portfolio return (SMB), of the high minus low portfolio return (HML), and of the momentum portfolio return (MOM). Furthermore, adapting these definitions for a sample of international banks is not trivial and would require significant assumptions. The alternative of using the regular factors calibrated for U.S. non-financial firms does not seem entirely reasonable, and it might bias the results in uncertain directions. Finally, Schuermann and Stiroh (2006) show that the market factor plays a central role in explaining bank returns when compared with the Fama-French factors. Taking all these factors into account, we considered that it would be more prudent to use a one-factor model in the estimation of idiosyncratic returns, while still respecting the intuition behind the instrumental-variables approach used by Leary and Roberts (2014).

in these strategies simultaneously, there is naturally an increase in systemic risk. As discussed by Ratnovski (2009) and Rochet and Tirole (1996), a lender of last resort is not necessarily going to bail out one bank that gets into trouble because of its own idiosyncratic wrong choices (unless this bank is clearly too big or too systemic to fail). However, if several banks are at risk, the lender of last resort needs to take the necessary actions to contain systemic risk. In this case, the likelihood of a bailout should increase, as if one of these banks gets into trouble, other banks will likely follow very soon, thus becoming too many to fail (Acharya and Yorulmazer 2007). Given this incentive structure, a given bank in that country clearly has high incentives to engage in similar risky but profitable strategies. However, the same cannot be said for a bank operating in another country, where there is a different lender of last resort. This reasoning justifies our choice for the reference peer group. Nevertheless, we will later relax this restriction and test other possible peer groups.

Using the two approaches, we are able to identify peer effects, after having dealt with the reflection problem through the use of instrumental variables. However, given that identification hinges on the quality of the instrument, we considered alternative approaches, discussed in detail in section 5.2.2. These include using another instrument inspired by the social multiplier approach proposed by Glaeser, Scheinkman, and Sacerdote (2003) and Sacerdote (2011).

5.2 Empirical Results

Table 4 presents the results of the first instrumental-variable approach in the estimation of peer effects in liquidity risk management.

In the first two columns we present the results of the estimation of equation (2). Hence, in these columns the peer effects are included in the regressions without properly addressing the reflection problem discussed before. When running this simple, yet possibly biased, estimation, we find strong evidence of positive peer or herding effects in individual banks' choices for the two liquidity indicators. The riskier are the funding and liquidity strategies of other banks in a given country, the riskier will tend to be the choices of each bank individually. However, as discussed above, these preliminary estimates may

Table 4. Regressions on Peer Effects in Liquidity Strategies

	Bank Peer Effects: Country-Year Peer Group (without IV)		Bank Peer Effects: Country-Year Peer Group (IV = Predicted Values of Rivals' Liquidity Ratios)			
			Second Step		First Step	
	Liquidity Creation	NSFR	Liquidity Creation	NSFR	Liquidity Creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Effects	0.81***	0.43***	0.56***	0.36	0.92***	0.24***
	(18.62)	(7.54)	(9.02)	(1.08)	(31.28)	(7.21)
Total Capital Ratio$_{t-1}$	−0.19**	0.08	−0.18***	0.08	0.03	−0.02
	(−2.29)	(0.91)	(−3.63)	(1.51)	(1.15)	(−0.83)
Log Assets$_t$	−1.73	−2.86**	−3.02***	−2.80***	−2.86***	0.87***
	(−1.61)	(−2.56)	(−4.95)	(−4.77)	(−10.22)	(3.47)
Net Interest Margin$_{t-1}$	−1.08***	1.90***	−1.17***	1.94***	−0.29***	0.41***
	(3.26)	(5.28)	(−5.71)	(7.18)	(−2.76)	(4.39)
Return on Assets$_{t-1}$	0.56	−1.34***	0.60***	−1.36***	−0.05	−0.19*
	(1.59)	(−3.46)	(2.60)	(−5.25)	(−0.39)	(−1.85)
Cost-to-Income$_{t-1}$	0.05***	−0.04*	0.06***	−0.04***	0.02***	−0.02***
	(2.64)	(−1.81)	(4.43)	(−2.80)	(2.79)	(−2.93)
Net Loans to Total Assets$_{t-1}$	0.26***	0.12**	0.26***	0.12***	0.04**	−0.01
	(6.34)	(2.18)	(9.17)	(3.72)	(2.54)	(−0.99)
Lons to Customer Deposits$_{t-1}$	0.00	−0.08***	0.00	−0.08***	−0.02***	0.00
	(0.43)	(−6.02)	(−0.51)	(−10.95)	(−6.33)	(0.63)
Liquidity Ratio$_{t-1}$	0.12***	0.05*	0.15***	0.05**	0.12***	0.04***
	(4.34)	(1.90)	(6.72)	(2.22)	(11.05)	(−4.50)
Liquidity Creation$_{t-1}$	—	−0.13***	—	−0.13***	—	−0.04***
	—	(−3.79)	—	(−5.92)	—	(−4.65)

(continued)

Table 4. (Continued)

	Bank Peer Effects: Country-Year Peer Group (without IV)		Bank Peer Effects: Country-Year Peer Group (IV = Predicted Values of Rivals' Liquidity Ratios)			
			Second Step		First Step	
	Liquidity Creation	NSFR	Liquidity Creation	NSFR	Liquidity Creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)
$NSFR_{t-1}$	−0.12***	—	−0.13***	—	−0.03***	—
	(−4.53)	—	(−7.58)	—	(−3.84)	—
Constant	69.7	72.8	−137.2**	119.3	−100.9***	587.8***
	(1.27)	(1.31)	(−2.44)	(0.54)	(−3.84)	(39.78)
Number of Observations	7,019	7,019	7,012	7,012	7,012	7,012
Number of Banks	1,737	1,737	1,736	1,736	1,736	1,736
F-test	127.9	37.7	—	—	785.0	308.7
R2 Within	0.477	0.186	0.467	0.186	0.705	0.484
R2 Between	0.329	0.501	0.095	0.524	0.399	0.555
R2 Overall	0.331	0.455	0.055	0.471	0.313	0.494

Notes: All regressions include year, country-year, and bank fixed effects. t-statistics are in parentheses. Peers are defined as the $j \neq i$ banks operating in the same country and in the same year as bank i. Columns 1 and 2 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 3 and 4 show the results of the instrumental-variables regressions (one for each liquidity indicator), where the instruments are the predicted values of peers' liquidity ratios. These predicted values result from the estimation of the regressions in table 3. Columns 5 and 6 show the first-stage estimation results for these three instrumental-variables regressions. The total capital ratio is calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets is computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks' operational costs (overheads) as a percentage of income generated before provisions. Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the net stable funding ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assets that need to be funded). These two variables are negatively correlated (i.e., more liquidity risk is associated with higher liquidity creation and lower NSFR) and are defined in detail in the data appendix. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level, respectively.

not be dealing adequately with the endogeneity problem underlying the estimation of peer effects.

The second group of columns (3–4) displays our main empirical results when explicitly dealing with the endogeneity problem created by considering peer effects. When we use the predicted values of peers' liquidity indicators as instruments, we conclude that the results presented in the first columns are no longer significant for the NSFR. For liquidity creation, peer effects continue to be strongly statistically significant. We obtain a coefficient of 0.56, meaning that one standard deviation in the average liquidity creation of peer banks will increase the liquidity creation of a given bank by 0.56 standard deviations. The different results obtained when the endogeneity problem is addressed are an indication that neglecting endogeneity in peer effects may lead to biased and incorrect results.

As discussed above, a good instrument should have an important contribution in explaining the potentially endogenous variable—i.e., the average peers' liquidity choices—but it should not directly affect the dependent variable. In the previous subsection we discussed why the latter condition holds in our setting, whereas in the last group of columns of table 4 we show that the chosen instrument is strongly statistically significant in both regressions.

Table 5 shows the results using our second identification strategy, based on Leary and Roberts (2014). Even though the subsample of listed banks used to compute this alternative estimation of peer effects is much smaller than the original (roughly one-quarter), we are still able to obtain statistically significant peer effects. In this case, the results are significant not only for liquidity creation but also for the NSFR. However, the statistical significance of the results is weaker. In terms of economic significance, the peer effects coming from the NSFR are very similar to those obtained from liquidity creation in table 4 (0.59, compared to 0.56 in table 4). However, the magnitude of the peer effects for liquidity creation is much larger with this identification strategy (1.28). Nevertheless, it is important to note that this coefficient is more imprecisely estimated, due to the lower statistical significance.[9]

[9]The sample used in table 5 is much smaller than that used in table 4. The difference in the significance and magnitude of peer effects between these two tables could thus be due to the difference in the way peer effects are measured

Table 5. Regressions on Peer Effects in Liquidity Strategies Using an Alternative Identification Strategy (Leary and Roberts 2014)

	Bank Peer Effects: Country-Year Peer Group (without IV)		Bank Peer Effects: Country-Year Peer Group			
			Second-Step Regressions		First-Step Regressions	
	Liquidity Creation	NSFR	Liquidity Creation	NSFR	Liquidity Creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Effects	0.53***	0.48***	1.28*	0.59**	0.00***	0.01***
	(4.31)	(5.31)	(1.70)	(2.00)	(−3.71)	(9.52)
Total Capital Ratio$_{t-1}$	−0.69***	0.43***	−0.66***	0.44***	−0.06	−0.06
	(−4.23)	(3.50)	(−5.21)	(4.21)	(−1.35)	(−1.61)
Log Assets$_t$	−2.57	−2.32	−1.85	−2.20**	−0.96**	−1.16***
	(−0.76)	(−1.61)	(−1.26)	(−2.00)	(−2.09)	(−3.13)
Net Interest Margin$_{t-1}$	−0.31	2.55***	−0.11	2.59***	−0.25	−0.46***
	(−0.32)	(4.72)	(−0.19)	(5.88)	(−1.34)	(−3.07)
Return on Assets$_{t-1}$	1.11	−1.98***	1.73**	−2.04***	−0.82***	0.58***
	(1.41)	(−3.46)	(2.15)	(−4.57)	(−4.51)	(4.01)
Cost-to-Income$_{t-1}$	0.11***	−0.06*	0.13***	−0.06***	−0.03***	0.01*
	(2.66)	(−1.82)	(3.86)	(−3.05)	(−3.52)	(1.75)
Net Loans to Total Assets$_{t-1}$	0.28***	0.28***	0.26***	0.29***	0.02	−0.05**
	(3.02)	(3.21)	(3.70)	(4.75)	(0.87)	(−2.39)
Loans to Customer Deposits$_{t-1}$	−0.02	−0.16***	0.03	−0.16***	−0.07***	0.02**
	(−0.56)	(−5.18)	(0.56)	(−7.75)	(−7.06)	(2.51)
Liquidity Ratio$_{t-1}$	0.31***	0.01	0.22**	0.01	0.13***	0.02
	(3.69)	(0.21)	(1.97)	(0.26)	(6.51)	(1.01)
Liquidity Creation$_{t-1}$	—	−0.28***	—	−0.28***	—	0.03**
	—	(−5.07)	—	(−7.37)	—	(1.99)

(*continued*)

Table 5. (Continued)

	Bank Peer Effects: Country-Year Peer Group (without IV)		Bank Peer Effects: Country-Year Peer Group — Second-Step Regressions		Bank Peer Effects: Country-Year Peer Group — First-Step Regressions	
	Liquidity Creation	NSFR	Liquidity Creation	NSFR	Liquidity Creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)
$NSFR_{t-1}$	−0.17***	—	−0.14***	—	−0.03**	—
	(−2.75)	—	(−2.93)	—	(−2.18)	—
Constant	−300.2*	185.4**	437.8	115.1	−987.7***	652.3***
	(−1.80)	(2.30)	(0.59)	(0.58)	(−56.12)	(46.40)
Number of Observations	1,986	1,986	1,986	1,986	1,986	1,986
Number of Banks	428	428	428	428	428	428
R2 Within	0.492	0.319	0.453	0.318	0.000	0.000
R2 Between	0.010	0.073	0.056	0.441	0.131	0.610
R2 Overall	0.001	0.063	0.050	0.407	0.053	0.494

Notes: All regressions include year, country-year, and bank fixed effects. t-statistics are in parentheses. Peers are defined as the $j \neq i$ banks operating in the same country and in the same year as bank i. Columns 1 and 2 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 3 and 4 show the results of the instrumental-variables regressions (one for each liquidity indicator), where the instruments are the idiosyncratic component of peer banks' equity returns (computed as the difference between the bank's returns and those of the S&P banks index in a given year). Columns 5 and 6 show the first-stage estimation results for these three instrumental-variables regressions. The total capital ratio is calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets is computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks' operational costs (overheads) as a percentage of income generated before provisions. Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the net stable funding ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assets that need to be funded). These two variables are negatively correlated (i.e., more liquidity risk is associated with higher liquidity creation and lower NSFR) and are defined in detail in the data appendix. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level, respectively.

5.2.1 Who Follows Whom: Alternative Peer Group Definitions

One key issue in the analysis of peer effects is the definition of an appropriate peer group (Manski 2000). So far we have assumed that the relevant peer group for collective risk-taking behaviors are the other banks in the same country. This hypothesis is anchored in the theoretical framework of Farhi and Tirole (2012) and Ratnovski (2009), which guides our analysis. Given that banks operating in the same country share the same lender of last resort, we argue that they likely share common beliefs about the likelihood of being bailed out in case of heightened systemic risk. However, it is possible that bailout probabilities are not the same for all banks in the same country. Actually, Farhi and Tirole (2012) show that this is true and argue that regulation should be applied only to a subset of key institutions that benefit from these implicit support guarantees, thus having incentives to take excessive risk.

To address these concerns, in table 6 we test alternative peer group definitions, in order to gain more insights about where collective risk-taking behaviors are coming from.

The first very simple exercise is to explore time dynamics within our baseline peer group definition. Until now we have assumed that banks make their decisions contemporaneously. However, it is possible that there are dynamic and lagged effects that are not being captured when using this definition. To check that, we run our estimations using lagged peer effects. The results obtained are very similar, suggesting that there is some persistency in banks' strategic interactions.

An additional possibility is to consider that banks focus on peer groups outside borders, implying that the lender of last resort may not be the only factor motivating excessive risk-taking in liquidity management. For example, large international players may follow similar strategies because they are competing to achieve higher returns on equity, possibly through riskier funding and liquidity strategies. To test this additional hypothesis, we consider as peers

---

or to the different sample used. To clarify this issue, we estimated our baseline peer effect estimation (table 4) using the sample of listed firms used for the estimation of the results reported in table 5. The results using this smaller sample are broadly consistent with those of table 4, thus suggesting that the differences in the results come mainly from identification strategy used rather than from the decrease in sample size.

Table 6. Regressions on Peer Effects in Liquidity Strategies—Robustness on Peer Group Definition

	Bank Peer Effects: Country-Year Peer Group (without IV)		Bank Peer Effects (with IV): Second-Step Regressions	
	Liquidity Creation	NSFR	Liquidity Creation	NSFR
	(1)	(2)	(3)	(4)
Baseline				
Peer Effects	0.81***	0.43***	0.56***	0.36
	(18.62)	(7.54)	(9.02)	(1.08)
Lagged Peers				
Peer Effects	0.38***	0.03	0.74***	0.79
	(5.83)	(0.65)	(6.00)	(0.67)
Peers as Other Banks (in Other Countries) in the Same Quartile				
Peer Effects	0.82***	0.21***	0.30	−0.11
	(9.50)	(3.59)	(1.22)	(−0.39)
Large Banks (Fourth Quartile in Each Country)				
Peer Effects	0.40***	0.27***	0.10	0.35***
	(5.97)	(4.40)	(0.33)	(5.05)
Large Banks (Fourth Quartile in the Sample)				
Peer Effects	0.30***	0.23***	1.60*	0.21*
	(4.83)	(4.12)	(1.67)	(1.69)
Only Larger Banks (Third and Fourth Quartiles)				
Peer Effects	0.63***	0.39***	0.59***	0.33**
	(10.45)	(7.38)	(6.64)	(2.46)
Only Smaller Banks (First and Second Quartiles)				
Peer Effects	0.75***	0.34***	0.98**	0.16
	(12.19)	(4.14)	(1.98)	(1.50)
Only Larger Banks (Top Five in Each Country)				
Peer Effects	0.15*	0.17**	−0.04	0.26
	(1.78)	(2.27)	(−0.12)	(1.27)
Only Larger Banks (Banks Classified as SIFIs)				
Peer Effects	−0.03	0.21	−0.27	0.48
	(−0.14)	(1.11)	(−0.52)	(1.27)
Only Larger Banks (Banks that Belong to the EURIBOR Panel)				
Peer Effects	0.46**	0.17*	−0.37	0.38*
	(2.55)	(1.70)	(−0.38)	(1.87)

(*continued*)

Table 6. (Continued)

	Bank Peer Effects: Country-Year Peer Group (without IV)		Bank Peer Effects (with IV): Second-Step Regressions	
	Liquidity Creation	NSFR	Liquidity Creation	NSFR
	(1)	(2)	(3)	(4)
Excluding Larger Banks (Top Five in Each Country)				
Peer Effects	0.76***	0.40***	0.58***	−0.55
	(14.15)	(6.40)	(9.01)	(−0.81)
Small Banks Following Large Banks (Fourth Quartile)				
Peer Effects	0.59***	−0.01	−0.41**	−0.15**
	(7.41)	(−0.24)	(−2.35)	(−2.15)
Small Banks Following Large Banks (Top Five)				
Peer Effects	−0.84***	−0.30***	−1.38***	−0.27***
	(−9.66)	(−7.13)	(−4.33)	(−5.71)
Small Banks Following Large Banks (SIFI List)				
Peer Effects	−0.47***	0.00	−1.84***	0.33***
	(−5.82)	(−0.01)	(−14.06)	(3.42)
Small Banks Following Large Banks (EURIBOR Panel)				
Peer Effects	−0.21***	−0.03	−0.86***	−0.30***
	(−3.41)	(−0.51)	(−9.77)	(−4.92)

Notes: t-statistics are in parentheses. Each line shows the coefficients for peer effects for different robustness tests. Bank quartiles were defined based on banks' total assets. Top five refers to the banks classified as being in the top five by assets in each country in Bankscope. The list of SIFIs (systemically important financial institutions) is the one disclosed by the Financial Stability Board in 2011. Columns 1 and 2 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 3 and 4 show the results of the instrumental-variables regressions, where the instruments are the predicted values of peers' liquidity ratios. These predicted values result from the estimation of the regressions in table 3. All the regressions use the same control variables as those reported in table 5. All regressions include year, country-year, and bank fixed effects. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level, respectively.

all the other banks of the same size quartile, regardless of their country of origin. This seems to be implausible, as peer effects are not statistically significant in any of the indicators analyzed. Collective risk-taking strategies seem to play a role mainly at the national level, possibly reflecting common lender of last resort beliefs previously discussed.

Another possibility is that the lender of last resort may only be willing to support banks that are too big or too systemic to fail, even if several banks are taking risks at the same time. Hence, it is possible that herding incentives are stronger for larger banks. To test this, we run our regressions only for the largest banks in the sample, defined as those in the fourth quartile of the total assets distribution in each country. When we use instrumental variables for the identification of peer effects, we continue to obtain evidence supporting the existence of collective risk-taking strategies. However, the results are now significant only for the NSFR.

A bank that is very large within borders may be a small bank in international terms. This should be especially true in smaller countries, with smaller banking systems. We might argue that large internationally active banks could also act as a peer group. To take that into account, we estimate the same regressions for the largest banks, but now defined as those in the fourth quartile of the worldwide total assets distribution. We still find evidence of peer effects, but remarkably weaker, thus providing further evidence that collective risk-taking is important mainly within borders.

To further examine the role of peer effects among larger banks, we compare peer effects estimates for banks above the median with those below. The statistical significance of peer effects is more robust for the largest banks, though there is also significant evidence of herding among the smaller banks. However, when only the five largest banks in each country are considered, the results on peer effects vanish entirely. Taking all this together, peer effects seem to be more prevalent among large banks, though not the largest ones.

Estimating peer effects for only the smallest banks also allows us to exclude large internationally active banks from the sample. These banks may have complex liquidity risk management strategies, with cross-border implications. As we still obtain statistically significant peer effects for these smaller banks, we can be confident that our results are not being influenced by these large international players having sophisticated risk management and hedging tools.

Even though the pre-crisis debate on systemic risk focused essentially on bank size, the global financial crisis made it clear that a small or medium-sized institution can also be systemic if, for instance, it is too interconnected to fail. Given this, size may be an imperfect measure of systemic risk. Indeed, the Basel Committee considers that systemically important banks should be identified using five different sets of indicators, taking into account (i) cross-jurisdictional activity, (ii) size, (iii) interconnectedness, (iv) substitutability, and (v) complexity.[10] Each set of indicators has an equal weight of 20 percent. That said, size is only one of the dimensions that allows identifying a systemically important institution. However, the other four dimensions rely on a set of indicators that are generally not publicly available. Against this background, we also considered the list of systemically important financial institutions (SIFIs) disclosed by the Financial Stability Board, in order to test whether there are significant peer effects within this group of banks. The results for these very large institutions are also weaker than for the initial large banks definition. In addition, we also considered the set of banks that belong to the EURIBOR panel, which may be seen as an alternative list of systemic financial institutions. In this case, the results are marginally significant only for the NSFR.

In sum, when we consider stricter definitions of large banks, such as banks that are classified among the top five in each country, banks belonging to the systemically important financial institutions (SIFIs) list disclosed by the Financial Stability Board, or banks in the EURIBOR panel, the results are relatively weaker. This is not surprising, as these are the banks that have fewer incentives to engage in collective risk-taking strategies. Indeed, these very large banks are generally too big to fail, benefiting permanently from implicit bailout guarantees. As such, these banks are the ones that face lower incentives to engage in riskier strategies when other banks are doing so, given that their probability of being bailed out hardly changes. Indeed, when we exclude the top five banks from the estimation, the results remain virtually unchanged, thus showing that herd behavior is not dominated by the largest banks.

Given these results, another important dimension to test is whether small banks tend to replicate the behavior of the larger banks. These smaller banks are those that could benefit more from engaging in collective risk-taking strategies, as argued above, most notably when larger banks are already taking more risk, thereby increasing the likelihood of systemic distress (Dávila and Walther

[10] http://www.bis.org/publ/bcbs255.pdf.

2017). Using different definitions of small and large banks, we obtain evidence of significant peer effects. However, in contrast to what we could expect initially, we obtain negative peer effects in some specifications for liquidity creation and for the NSFR in most specifications. This means that, in these cases, small banks actually decrease liquidity risk when the largest banks are increasing it. Collective risk-taking strategies are not prevalent among the smaller banks. These banks do not seem to replicate liquidity risk management strategies between themselves, nor replicate those of the largest banks.

Summing up what we have learned so far from considering different definitions of peer groups and peer interactions based on bank size and systemic importance, we can claim that peer effects are stronger for larger banks, though not for the largest of them all. This is consistent with the view that the largest banks are too big to fail and expect to be bailed out in any circumstance. In turn, smaller banks will hardly ever be bailed out. However, relatively large banks, just below the top ones, might expect to be bailed out in exceptional circumstances. This would be the case if systemic risk and contagion fears are heightened. In such a scenario, the likelihood of a bailout in case of distress might increase, as the responsible authorities will be worried about mitigating contagion. This creates incentives for banks to engage in collective risk-taking strategies. If every player adopts similar strategies, it will be hard to single out one institution for excessive risk-taking, thus making a bailout more justifiable (Farhi and Tirole 2012; Ratnovski 2009).

5.2.2 Robustness Analysis

To better understand how these peer effects work and to ensure that the results are consistent under a wide set of specifications, we run a large battery of robustness tests.

Table 7 reports some of the most important tests conducted. All the estimations were performed without and with instrumental variables, in columns 1–2 and 3–4, respectively.

Given the challenges of peer effects estimation (Angrist 2014; Manski 1993, 2000), we begin by testing alternative identification strategies.

First, we consider an adapted version of our identification strategy based on the social multiplier proposed by Glaeser, Scheinkman, and Sacerdote (2003) and Sacerdote (2011). The basic idea is to

Table 7. Regressions on Peer Effects in Liquidity Strategies—Robustness

	Bank Peer Effects: Country-Year Peer Group (without IV)		**Bank Peer Effects (with IV): Second-Step Regressions**	
	Liquidity Creation	**NSFR**	**Liquidity Creation**	**NSFR**
	(1)	**(2)**	**(3)**	**(4)**
Baseline				
Peer Effects	0.81***	0.43***	0.56***	0.36
	(18.62)	(7.54)	(9.02)	(1.08)
Peer Effects Using Predicted Values (without IV)				
Peer Effects	0.51***	0.09	—	—
	(8.32)	(1.06)		
Accounting for Predicted Regressors with Bootstrapped Standard Errors				
Peer Effects	0.81***	0.43***	0.56***	0.34
	(17.13)	(7.62)	(4.74)	(0.81)
Before the Crisis				
Peer Effects	0.46***	0.12	0.35***	0.33*
	(5.24)	(1.54)	(2.74)	(1.94)
Removing Banks with Asset Growth above 50 Percent				
Peer Effects	0.79***	0.39***	0.53***	0.42***
	(17.94)	(7.00)	(7.97)	(2.60)
Excluding U.S. Banks				
Peer Effects	0.24***	0.19***	−1.87	0.28*
	(2.92)	(2.94)	(−1.47)	(1.95)
Excluding Smaller Countries (Less than Fifty Observations)				
Peer Effects	0.84***	0.46***	0.56***	0.25
	(18.78)	(7.06)	(10.60)	(1.06)
Western Europe Banks				
Peer Effects	0.24**	0.19***	−10.43	0.24
	(2.45)	(2.79)	(−0.42)	(0.43)
Eastern Europe Banks				
Peer Effects	0.20	0.13	0.28	0.25*
	(1.59)	(1.22)	(0.26)	(1.73)
U.S., Canada, and Western Europe Banks				
Peer Effects	0.79***	0.43***	0.63***	0.23
	(13.12)	(6.60)	(8.78)	(1.47)
Excluding Countries More Directly Affected during the Global Crisis				
Peer Effects	0.21**	0.15**	−1.35	0.18
	(2.41)	(2.06)	(−1.48)	(1.18)

(*continued*)

Table 7. (Continued)

	Bank Peer Effects: Country-Year Peer Group (without IV)		Bank Peer Effects (with IV): Second-Step Regressions	
	Liquidity Creation	**NSFR**	**Liquidity Creation**	**NSFR**
	(1)	**(2)**	**(3)**	**(4)**
Euro Area as One Peer Group				
Peer Effects	0.85***	0.47***	1.29***	4.00
	(18.87)	(7.49)	(10.47)	(0.68)
Without Country-Year Fixed Effects				
Peer Effects	0.81***	0.43***	0.43***	0.36
	(18.62)	(7.54)	(3.46)	(1.08)
With Country and Year Fixed Effects (Random-Effects Estimation)				
Peer Effects	0.78***	0.37***	0.46***	0.02
	(19.34)	(6.95)	(5.21)	(0.11)
Without Liquidity Controls				
Peer Effects	0.81***	0.41***	0.54***	0.25
	(19.91)	(6.90)	(8.58)	(0.44)
Controlling for Leverage (instead of Capital Ratio)				
Peer Effects	0.76***	0.46***	0.66***	0.23***
	(21.44)	(9.97)	(16.09)	(3.50)
Only after 2004				
Peer Effects	0.89***	0.53***	0.58***	0.45**
	(20.90)	(9.01)	(6.41)	(2.31)
Lagged Dependent Variables				
Peer Effects	0.76***	0.42***	0.55***	0.00
	(18.14)	(7.90)	(8.87)	(0.00)
Peers Weighted by Size				
Peer Effects	0.82***	0.44***	0.51***	0.27
	(18.04)	(7.41)	(4.33)	(0.81)

Notes: Peers are defined as the $j \neq i$ banks operating in the same country and in the same year as bank i. t-statistics are in parentheses. Each line shows the coefficients for peer effects for different robustness tests. In the regressions with bootstrapped standard errors, two year dummies had to be excluded. The pre-crisis period refers to the years 2002–06. Countries considered as most directly affected by the global financial crisis include the United States, Iceland, Greece, Ireland, Portugal, Spain, and Italy. Columns 1 and 2 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 3 and 4 show the results of the instrumental-variables regressions, where the instruments are the predicted values of peers' liquidity ratios. These predicted values result from the estimation of the regressions in table 3. All the regressions use the same control variables as those reported in table 5. All regressions include year, country-year, and bank fixed effects. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level, respectively.

use the peer group average of the predicted values arising from the regressions on liquidity determinants directly in the peer effects regressions (equation (1)), instead of using them as instruments for the peer effects.[11] The results of this alternative estimation approach confirm the existence of peer effects, though only for liquidity creation.

A potentially relevant econometric issue is related with the use of predicted regressors in the estimations. To be sure that this is not affecting the results, we present the results using bootstrapped standard errors.[12] The results are generally consistent.

For robustness, we exclude the crisis period in order to focus the analysis on possible peer effects in the years before the global financial crisis. The peer effect coefficient for liquidity creation remains significant, while for the NSFR we now have marginally significant results when using instrumental variables. This shows that collective risk-taking behaviors were more prevalent before the crisis.

In addition, we remove from the sample banks with year-on-year asset growth above 50 percent, as these banks may have been involved in mergers and acquisitions. Our results become significantly stronger in this case, most notably for the NSFR.

U.S. banks represent slightly more than three-quarters of the sample. In order to ensure that the results are not influenced by this, we exclude all U.S. banks from the estimation. In this case, we obtain statistically significant effects only for the NSFR. In addition, we also estimate the regressions separately for Western and Eastern European banks, and for U.S., Canadian, and Western European banks together. The results are not statistically significant when only Western European banks are considered and are marginally significant for Eastern European banks. All this suggests that collective

[11] Our estimates of the social multiplier are an adaptation because of the level of aggregation considered. As discussed by Glaeser, Scheinkman, and Sacerdote (2003), several levels of aggregation may be considered in the estimations of the social multiplier. In our case, we use the coefficients from an individual-level regression to predict aggregate-level outcomes for the peer group of each bank. We then regress observed individual outcomes on these aggregate predicted values to obtain the social multiplier.

[12] The estimated coefficients display minor differences because it was necessary to exclude two year dummies from the estimations, in order to obtain the degrees of freedom necessary for the bootstrapping.

risk-taking strategies in the run-up to the crisis were more prevalent among U.S. banks.

Furthermore, we exclude the countries more directly affected by the global financial crisis from the regressions (United States, Iceland, Greece, Ireland, Portugal, Spain, and Italy). When banks from these countries are excluded, we obtain no evidence for collective risk-taking strategies, suggesting that the countries more severely hit by the crisis were indeed those where these behaviors were more prevalent.

Given the strong financial integration in the euro area, we also tested whether banks operating in euro-area countries behave as a peer group. The results are consistent with the baseline specification, showing that it is indifferent considering euro-area members individually or as a single group. When all banks in our sample are considered, we obtain statistically significant peer effects on liquidity creation regardless of whether we consider euro-area banks as one single peer group or as separate country-level peer groups.

For robustness purposes, we also run our estimates without using country-year fixed effects, with separate country and year fixed effects (using random-effects estimation), and without controlling for liquidity indicators. In all cases the results are robust.

In our baseline specification we used the total capital ratio as an explanatory variable. However, the global financial crisis showed that, in many cases, the leverage ratio was better able to capture the financial situation of banks. To address this issue we estimated the peer effect regressions using the leverage ratio (measured as equity over total assets) instead of the total capital ratio. The results are stronger, as the peer effects on the NSFR become statistically significant and increase for liquidity creation.

We also consider data only from 2004 on, in order to avoid using accounting information that is time inconsistent, given that in many countries common accounting reporting standards (IFRS) were introduced around this time. The results become generally stronger.

Finally, we estimated the models including a lagged dependent variable and weighting peers by their size. The results are qualitatively and quantitatively consistent in both cases.

All in all, the robustness analysis points to consistent evidence of significant peer effects in liquidity risk decisions.

Table 8. Peer Effects by Year

	Bank Peer Effects: Country-Year Peer Group (IV = Predicted Values of Rivals' Liquidity Ratios) Second-Step Regressions		Bank Peer Effects: Country-Year Peer Group (IV = Idiosyncratic Equity Returns) Second-Step Regressions	
	Liquidity Creation	**NSFR**	**Liquidity Creation**	**NSFR**
	(1)	**(2)**	**(3)**	**(4)**
Full Sample	0.56***	0.36	1.28*	0.59**
	(9.02)	(1.08)	(1.70)	(2.00)
2003	0.52***	0.14*	0.61	−5.54
	(8.44)	(1.92)	(1.60)	(−0.35)
2004	0.38***	0.18**	−3.75	−2.36*
	(4.89)	(2.04)	(−0.59)	(−1.77)
2005	0.51***	0.03	1.51	0.34
	(6.49)	(0.44)	(0.74)	(0.37)
2006	0.68***	−0.04	0.80	3.08
	(12.93)	(−0.94)	(1.01)	(0.30)
2007	0.74***	−0.08*	0.28	0.43**
	(14.01)	(−1.66)	(0.85)	(2.51)
2008	0.76***	0.09**	−0.10	0.38
	(14.18)	(2.02)	(−0.29)	(1.28)
2009	0.13	0.21***	−3.49	0.73***
	(1.25)	(3.69)	(−0.87)	(3.42)

Notes: t-statistics are in parentheses. Each line shows the coefficients for peer effects for different years. All the regressions use the same control variables as those reported in table 4. All regressions include year, country-year, and bank fixed effects. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level, respectively.

5.2.3 Peer Effects by Year

In section 3.2, we looked into the evolution and dispersion of liquidity indicators in the run-up to the global financial crisis, observing that there was a general deterioration in liquidity indicators during this period. In this subsection, we estimate peer effects for each year. The results are in table 8.

In terms of statistical significance, when we consider as instruments the predicted values of liquidity indicators (columns 1 and 2), there were peer effects in almost all years in liquidity creation, with the exception of 2009. The results are somewhat weaker for the

NSFR. When we use the idiosyncratic component of equity returns as an instrument as in Leary and Roberts (2014), thereby focusing on a smaller subsample of publicly listed banks, the results are slightly weaker, though there is still statistically significant evidence of peer effects in the NSFR (columns 3 and 4).

Looking at the economic significance of the estimated peer effects, some interesting conclusions may be drawn. Peer effects were greater in the years immediately before the global financial crisis. For instance, in 2007 the peer effects estimated for liquidity creation were 0.74, which compares with an average estimate for the whole sample of 0.56. This suggests that there were indeed observable collective risk-taking behaviors right before the global financial crisis, which possibly made banks more vulnerable to the shocks they later faced. It is also interesting to note that there were significant peer effects during the crisis years, when banks were simultaneously reshaping their balance sheets to manage risks in the new environment in which they were operating, marked by heightened funding pressures and deleveraging incentives.

6. Concluding Remarks and Policy Implications

Banks' liquidity risk was at the core of the global financial crisis in its early days. By transforming liquid liabilities (deposits) into illiquid claims (loans), banks are intrinsically exposed to funding liquidity risk, though this risk materializes only occasionally. In this paper we provide empirical insight into how banks manage their liquidity risk and consider explicitly the role of collective risk-taking strategies on herding behavior. Indeed, when other banks are taking more risk, any given bank may have incentives to engage in similar strategies.

The empirical estimation of these peer effects among banks in such a framework raises some econometric challenges. Based on the arguments put forth by Manski (1993), if we consider that peer choices may affect the decisions of a specific bank, we cannot rule out that the decisions of that bank will not, in turn, affect the choices made by peers (reflection problem). To overcome this critical identification problem, we use two strategies based on instrumental variables. First, we consider as an instrument for peer effects the predicted values of liquidity indicators of peer banks based on the regressions of the determinants of liquidity indicators. These predicted values depend only on observable bank characteristics and should thus be orthogonal to systematic or herding effects. Second, we follow an empirical strategy based on Leary and Roberts (2014), using the idiosyncratic component of equity returns as an instrument for peer effects.

Using these two methodologies, we can find evidence of significant peer effects, which is strengthened by extensive robustness tests. Peer effects are stronger for larger banks, though not for the largest ones. The latter are typically perceived as being too big to fail and probably do not need to change their behavior when other banks are taking more risk. The smallest banks will hardly ever be bailed out. So, strategic interactions are stronger for large banks below the top tier, which do not expect to be bailed out under normal circumstances but may be so in a situation of heightened systemic risk, when a large bank failure could lead to a collapse in the financial system. These results lend empirical support to the theoretical findings of Farhi and Tirole (2012) and Ratnovski (2009).

Our results provide an important contribution to the ongoing policy debate. These collective risk-taking behaviors call for regulation to adequately align the incentives and minimize negative externalities. The collective behavior of banks transforms a traditionally microprudential dimension of banking risk into a macroprudential risk, which may ultimately generate much larger costs to the economy.

The Basel III regulatory framework is a huge step forward in the international regulation of banks. At the microprudential level, new liquidity requirements are going to be gradually imposed, reducing excessive maturity mismatches and ensuring that banks hold enough liquid assets to survive during a short stress period. However, our results suggest that there may be an element missing from the new regulatory framework: the systemic component of liquidity risk. The new liquidity risk regulation will ensure that, at the microprudential level, institutions are less exposed to liquidity risk. Nevertheless, additional macroprudential policy tools may eventually be considered to mitigate the incentives for collective risk-taking strategies. These may include tighter (cyclical or sectoral) liquidity regulation or limits to certain types of exposures or funding sources. Moreover, a well-functioning resolution and bail-in framework is critical to mitigate bailout expectations.

Data Appendix

Table 9. Definition of Liquidity Indicators

	Liquidity Creation		NSFR
	Classification	**Weights**	**Weights**
Assets			
Residential Mortgage Loans	SL	0	0.65
Other Mortgage Loans	SL	0	0.65
Other Consumer/Retail Loans	SL	0	0.85
Corporate and Commercial Loans	1	0.5	0.85
Other Loans	1	0.5	0.85
Less: Reserves for Impaired Loans/NPLs			−1.00
Net Loans			
Loans and Advances to Banks	SL	0	0.50
Reverse Repos and Cash Collateral			0.00
Trading Securities and at FV through Income			0.50
Derivatives			0.50
Available for Sale Securities			0.50
Held to Maturity Securities			1.00
At-Equity Investments in Associates			1.00
Other Securities			1.00
Total Securities	L	−0.5	
Investments in Property	1	0.5	1.00
Insurance Assets	1	0.5	1.00
Other Earning Assets	1	0.5	1.00
Total Earning Assets			
Cash and Due from Banks	L	−0.5	0.00
Foreclosed Real Estate	1	0.5	1.00
Fixed Assets	1	0.5	1.00
Goodwill	1	0.5	1.00
Other Intangibles	1	0.5	1.00
Current Tax Assets	1	0.5	1.00
Deferred Tax Assets	1	0.5	1.00
Discontinued Operations	1	0.5	1.00
Other Assets	1	0.5	1.00
Total Assets			
Liabilities			
Customer Deposits: Current	L	0.5	
Customer Deposits: Savings	L	0.5	
Customer Deposits: Term	SL	0	
Total Customer Deposits			0.85
Deposits from Banks	L	0.5	0.00
Repos and Cash Collateral	L	0.5	0.00
Other Deposits and Short-Term Borrowings	L	0.5	0.00

(*continued*)

Table 9. (Continued)

	Liquidity Creation		NSFR
	Classification	**Weights**	**Weights**
Total Deposits, Money Market and Short-Term Funding			
Total Long-Term Funding	1	−0.5	1.00
Derivatives	L	0.5	0.00
Trading Liabilities	L	0.5	0.00
Total Funding			
Fair Value Portion of Debt	SL	0.0	0.00
Credit Impairment Reserves	SL	0.0	0.00
Reserves for Pensions and Other	SL	0.0	0.00
Current Tax Liabilities	SL	0.0	0.00
Deferred Tax Liabilities	SL	0.0	0.00
Other Deferred Liabilities	SL	0.0	0.00
Discontinued Operations	SL	0.0	0.00
Insurance Liabilities	SL	0.0	0.00
Other Liabilities	SL	0.0	0.00
Total Liabilities			
Pref. Shares and Hybrid Capital Accounted for as Debt	1	−0.5	1.00
Pref. Shares and Hybrid Capital Accounted for as Equity	1	−0.5	1.00
Total Equity	1	−0.5	1.00
Total Liabilities and Equity			

Notes: Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. The variable is defined as

$$\begin{aligned} Liquidity\_creation &= \{1/2 * Illiq\_assets + 0 * Semi\_liq\_assets - 1/2 * Liq\_assets\} \\ &+ \{1/2 * Liq\_liab. + 0 * Semi\_liq\_liab. - 1/2 * Illiq\_liab.\} - 1/2 * Capital. \end{aligned}$$

Assets and liabilities are classified as liquid, semi-liquid, or illiquid based on the criteria used by Berger and Bouwman (2009). The classification for each accounting item is displayed in the table. Some assumptions were made, as the accounting classification is not identical to the one used in Berger and Bouwman (2009). We consider liquidity creation as a percentage of total assets.

NSFR is an approximation of the net stable funding ratio defined in Basel III, which considers the available stable funding relative to the required stable funding (i.e., assets that need to be funded). The higher this ratio is, the more comfortable is the institution's liquidity position. It is defined as

$$NSFR = \frac{Available\_stable\_funding}{Required\_stable\_funding} * 100.$$

Each accounting item was given a weight based on the Basel Committee's guidelines. However, it is important to note that this is a rough approximation, as the accounting data available on Bankscope do not allow for accurate classification of all the items. The weights chosen are presented in the table.

References

Acharya, V. 2009. "A Theory of Systemic Risk and Design of Prudential Bank Regulation." *Journal of Financial Stability* 5 (3): 224–55.

Acharya, V., H. Mehran, and A. Thakor. 2016. "Caught Between Scylla and Charybdis? Regulating Bank Leverage When There is Rent Seeking and Risk Shifting." *Review of Corporate Finance Studies* 5 (1): 36–75.

Acharya, V., H. Shin, and T. Yorulmazer. 2011. "Crisis Resolution and Bank Liquidity." *Review of Financial Studies* 24 (6): 2166–2205.

Acharya, V., and T. Yorulmazer. 2007. "Too Many to Fail—An Analysis of Time-Inconsistency in Bank Closure Policies." *Journal of Financial Intermediation* 16 (1): 1–31.

———. 2008. "Information Contagion and Bank Herding." *Journal of Money, Credit and Banking* 40 (1): 215–31.

Allen, F., A. Babus, and E. Carletti. 2012. "Asset Commonality, Debt Maturity and Systemic Risk." *Journal of Financial Economics* 104 (3): 519–34.

Allen, F., and D. Gale. 2004a. "Financial Fragility, Liquidity, and Asset Prices." *Journal of the European Economic Association* 2 (6): 1015–48.

———. 2004b. "Financial Intermediaries and Markets." *Econometrica* 72 (4): 1023–61.

Angrist, J. 2014. "The Perils of Peer Effects." *Labour Economics* 30 (October): 98–108.

Aspachs, O., E. Nier, and M. Tisset. 2005. "Liquidity, Banking Regulation and the Macroeconomy: Evidence on Bank Liquidity Holdings from a Panel of UK-Resident Banks." Working Paper, London School of Economics.

Barron, J., and N. Valev. 2000. "International Lending by U.S. Banks." *Journal of Money, Credit and Banking* 32 (3): 357–81.

Basel Committee on Banking Supervision. 2010. "Basel III: International Framework for Liquidity Risk Measurement, Standards and Monitoring."

Bengui, J. 2010. "Systemic Risk and Inefficient Debt Maturity." Mimeo.

Berger, A., and C. Bouwman. 2009. "Bank Liquidity Creation." *Review of Financial Studies* 22 (9): 3779–3837.

Bonner, C., I. van Lelyveld, and R. Zymek. 2015. "Banks' Liquidity Buffers and the Role of Liquidity Regulation." *Journal of Financial Services Research* 48 (3): 215–34.

Boot, A. 2011. "Banking at the Crossroads: How to Deal with Marketability and Complexity?" *Review of Development Finance* 1 (3–4): 167–83.

Borio, C. 2010. "Ten Propositions about Liquidity Crises." *CESifo Economic Studies* 56 (1): 70–95.

Bouwman, C. 2014. "Liquidity: How Banks Create It and How It Should Be Regulated." In *The Oxford Handbook of Banking*, 2nd edition, ed. A. N. Berger, P. Molyneux, and J. O. S. Wilson. Oxford University Press.

Bramoullé, Y., H. Djebbari, and B. Fortin. 2009. "Identification of Peer Effects through Social Networks." *Journal of Econometrics* 150 (1): 41–55.

Brown, C., and I. S. Dinç. 2011. "Too Many to Fail? Evidence of Regulatory Forbearance When the Banking Sector Is Weak." *Review of Financial Studies* 24 (4): 1378–1405.

Brown, J., Z. Ivkovic, P. Smith, and S. Weisbenner. 2008. "Neighbors Matter: Causal Community Effects and Stock Market Participation." *Journal of Finance* 63 (3): 1509–31.

Brunnermeier, M. 2009. "Deciphering the Liquidity and Credit Crunch 2007–2008." *Journal of Economic Perspectives* 23 (1): 77–100.

Brunnermeier, M., A. Crockett, C. Goodhart, A. Persaud, and H. Shin. 2009. *Geneva Report on the World Economy 11: The Fundamental Principles of Financial Regulation.* Brookings Institution Press.

Bryant, J. 1980. "A Model of Reserves, Bank Runs, and Deposit Insurance." *Journal of Banking and Finance* 4 (4): 335–44.

Calomiris, C., F. Heider, and M. Hoerova. 2013. "A Theory of Bank Liquidity Requirements." Mimeo.

Calomiris, C., and C. Kahn. 1991. "The Role of Demandable Debt in Structuring Optimal Banking Arrangements." *American Economic Review* 81 (3): 497–513.

Cao, J., and G. Illing. 2010. "Regulation of Systemic Liquidity Risk." *Financial Markets Portfolio Management* 24 (1): 31–48.

———. 2011. "Endogenous Exposure to Systemic Liquidity Risk." *International Journal of Central Banking* 7 (2, June): 173–216.

Carrell, S., R. Fullerton, and J. West. 2009. "Does Your Cohort Matter? Measuring Peer Effects in College Achievement." *Journal of Labor Economics* 27 (3): 439–64.

Committee on the Global Financial System. 2010. "Funding Patterns and Liquidity Management of Internationally Active Banks." CGFS Paper No. 39 (May).

Dávila, E., and A. Walther. 2017. "Does Size Matter? Bailouts with Large and Small Banks." NBER Working Paper No. 24132.

de Haan, L., and J. W. van den End. 2013. "Bank Liquidity, the Maturity Ladder, and Regulation." *Journal of Banking and Finance* 37 (10): 3930–50.

Deléchat, C., C. Henao, P. Muthoora, and S. Vtyurina. 2012. "The Determinants of Banks' Liquidity Buffers in Central America." IMF Working Paper No. 12/301.

Demirgüç-Kunt, A., and H. Huizinga. 2010. "Bank Activity and Funding Strategies: The Impact on Risk and Returns." *Journal of Financial Economics* 98 (3): 626–50.

Diamond, D., and P. Dybvig. 1983. "Bank Runs, Deposit Insurance, and Liquidity." *Journal of Political Economy* 91 (3): 401–19.

Diamond, D., and R. Rajan. 2000. "A Theory of Bank Capital." *Journal of Finance* 55 (6): 2431–65.

———. 2001a. "Banks and Liquidity." *American Economic Review* 91 (2): 422–25.

———. 2001b. "Liquidity Risk, Liquidity Creation, and Financial Fragility: A Theory of Banking." *Journal of Political Economy* 109 (2): 287–327.

———. 2005. "Liquidity Shortages and Banking Crises." *Journal of Finance* 60 (2): 615–47.

Dinger, V. 2009. "Do Foreign-Owned Banks Affect Banking System Liquidity Risk?" *Journal of Comparative Economics* 37 (4): 647–57.

Fama, E. F., and K. R. French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33 (1): 3–56.

Farhi, E., M. Golosov, and A. Tsyvinski. 2009. "A Theory of Liquidity and Regulation of Financial Intermediation." *Review of Economic Studies* 76 (3): 973–92.

Farhi, E., and J. Tirole. 2012. "Collective Moral Hazard, Maturity Mismatch, and Systemic Bailouts." *American Economic Review* 102 (1): 60–93.

Feinman, J. 1993. "Reserve Requirements: History, Current Practice, and Potential Reform." *Federal Reserve Bulletin* (June): 569–89.

Freixas, X., A. Martin, and D. Skeie. 2011. "Bank Liquidity, Interbank Markets, and Monetary Policy." *Review of Financial Studies* 24 (8): 2656–92.

Freixas, X., B. Parigi, and J. C. Rochet. 2004. "The Lender of Last Resort: A Twenty-first Century Approach." *Journal of the European Economic Association* 2 (6): 1085–1115.

Gale, D., and T. Yorulmazer. 2013. "Liquidity Hoarding." *Theoretical Economics* 8 (2): 291–324.

Glaeser, E., J. Scheinkman, and B. Sacerdote. 2003. "The Social Multiplier." *Journal of the European Economic Association* 1 (2/3): 345–53.

Gorton, G., and L. Huang. 2004. "Liquidity, Efficiency, and Bank Bailouts." *American Economic Review* 94 (3): 455–83.

Gropp, R., and F. Heider. 2010. "The Determinants of Bank Capital Structure." *Review of Finance* 14 (4): 587–622.

Holmstrom, B., and J. Tirole. 1998. "Private and Public Supply of Liquidity." *Journal of Political Economy* 106 (1): 1–40.

Huang, R., and L. Ratnovski. 2011. "The Dark Side of Bank Wholesale Funding." *Journal of Financial Intermediation* 20 (2): 248–63.

Jain, A., and S. Gupta. 1987. "Some Evidence on 'Herding' Behavior of U. S. Banks." *Journal of Money, Credit and Banking* 19 (1): 78–89.

Kashyap, A., R. Rajan, and J. Stein. 2002. "Banks as Liquidity Providers: An Explanation for the Coexistence of Lending and Deposit-taking." *Journal of Finance* 57 (1): 33–73.

Klein, M. 1971. "A Theory of the Banking Firm." *Journal of Money, Credit and Banking* 3 (2, Part 1): 205–18.

Leary, M., and M. Roberts. 2014. "Do Peer Firms Affect Corporate Financial Policy?" *Journal of Finance* 69 (1): 139–78.

Lee, L. 2007. "Identification and Estimation of Econometric Models with Group Interactions, Contextual Factors and Fixed Effects." *Journal of Econometrics* 140 (2): 333–74.

Malherbe, F. 2014. "Self-Fulfilling Liquidity Dry-Ups." *Journal of Finance* 69 (2): 947–70.

Manski, C. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *Review of Economic Studies* 60 (3): 531–42.

———. 2000. "Economic Analysis of Social Interactions." *Journal of Economic Perspectives* 14 (3): 115–36.

Perotti, E., and J. Suarez. 2002. "Last Bank Standing: What Do I Gain if You Fail?" *European Economic Review* 46 (9): 1599–1622.

Pierret, D. 2015. "Systemic Risk and the Solvency-Liquidity Nexus of Banks." *International Journal of Central Banking* 11 (3, June): 193–227.

Rajan, R. 2006. "Has Finance Made the World Riskier?" *European Financial Management* 12 (4): 499–533.

Ratnovski, L. 2009. "Bank Liquidity Regulation and the Lender of Last Resort." *Journal of Financial Intermediation* 18 (4): 541–58.

———. 2013. "Liquidity and Transparency in Bank Risk Management." *Journal of Financial Intermediation* 22 (3): 422–39.

Repullo, R. 2005. "Liquidity, Risk Taking, and the Lender of Last Resort." *International Journal of Central Banking* 1 (2, September): 47–80.

Rochet, J. C. 2004. "Macroeconomic Shocks and Banking Supervision." *Journal of Financial Stability* 1 (1): 93–110.

Rochet, J. C., and J. Tirole. 1996. "Interbank Lending and Systemic Risk." *Journal of Money, Credit and Banking* 28 (4): 733–62.

Rochet, J. C., and X. Vives. 2004. "Coordination Failures and the Lender of Last Resort: Was Bagehot Right after All?" *Journal of the European Economic Association* 2 (6): 1116–47.

Sacerdote, B. 2001. "Peer Effects with Random Assignment: Results for Dartmouth Roommates." *Quarterly Journal of Economics* 116 (2): 681–704.

———. 2011. "Peer Effects in Education: How Might They Work, How Big Are They and How Much Do We Know thus Far?" In *Handbook of the Economics of Education*, Vol. 3., ed. E. A. Hanushek, S. Machin, and L. Woessmann, 249–78 (chapter 4). Elsevier B.V.

Santos, J. A. C., and J. Suarez. 2018. "Liquidity Standards and the Value of an Informed Lender of Last Resort." Forthcoming in *Journal of Financial Economics*.

Schuermann, T., and K. Stiroh. 2006. "Visible and Hidden Risk Factors for Banks." Staff Report No. 252, Federal Reserve Bank of New York.

Silva, A. F. 2017. "Strategic Liquidity Mismatch and Financial Sector Stability." Forthcoming in *Review of Financial Studies.*

Strahan, P. 2008. "Liquidity Production in 21st Century Banking." NBER Working Paper No. 13798.

Tirole, J. 2011. "Illiquidity and All Its Friends." *Journal of Economic Literature* 49 (2): 287–325.

van den End, J., and M. Tabbae. 2012. "When Liquidity Risk Becomes a Systemic Issue: Empirical Evidence of Bank Behaviour." *Journal of Financial Stability* 8 (2): 107–20.

Vives, X. 2014. "Strategic Complementarity, Fragility, and Regulation." *Review of Financial Studies* 27 (12): 3547–92.

Wagner, W. 2007a. "Aggregate Liquidity Shortages, Idiosyncratic Liquidity Smoothing and Banking Regulation." *Journal of Financial Stability* 3 (1): 18–32.

———. 2007b. "The Liquidity of Bank Assets and Banking Stability." *Journal of Banking and Finance* 31 (1): 121–39.

Mixed-Frequency Models for Tracking Short-Term Economic Developments in Switzerland*

Alain Galli, Christian Hepenstrick, and Rolf Scheufele
Swiss National Bank

We compare several methods for monitoring short-term economic developments in Switzerland. Based on a large mixed-frequency data set, the following approaches are presented and discussed: a factor-based *information combination* approach (a dynamic factor model based on the Kalman filter/smoother and estimated by the EM algorithm), a *model combination* approach resting on MIDAS regression models, and a *variable selection* approach using a specific-to-general algorithm. In an out-of-sample GDP forecasting exercise, we show that the considered approaches clearly beat relevant benchmarks such as univariate time-series models and models that work with just one indicator. Moreover, we find that the factor model is superior to the other two approaches under investigation. However, forecast pooling of the three methods turns out to be even more promising.

JEL Codes: C32, C53, E37.

*We want to thank Luca Moretti, Massimiliano Marcellino, Lucrezia Reichlin, and three anonymous referees as well as participants at IAAE conference 2016 in Milano, the ISF 2016 in Santander, and the CIRET conference 2016 in Copenhagen for valuable comments. The views, opinions, findings, and conclusions or recommendations expressed in this paper are strictly those of the authors. They do not necessarily reflect the views of the Swiss National Bank. The SNB takes no responsibility for any errors or omissions in, or for the correctness of, the information contained in this paper. In particular, the models described in the paper are not part of the suite of models used for Swiss National Bank's inflation forecast, published on a quarterly basis in its Quarterly Bulletin. Authors' e-mails: alain.galli@snb.ch, christian.hepenstrick@snb.ch, and rolf.scheufele@snb.ch.

1. Introduction

Policy institutions such as central banks depend on the timely assessment of past, current, and future economic conditions. However, key statistics on economic conditions are often estimated infrequently and published with a substantial time delay. GDP, for example, is computed at the quarterly frequency. Looking across countries, the timeliest first estimates are published about one month after the reference quarter (e.g., in the United States, the euro area, the United Kingdom, and China), whereas for Switzerland, the publication lag of GDP is two months. Therefore, the problem of imperfect and incomplete information on the current state of the economy is more pronounced than for other developed economies: many of the main indicators that economists routinely use to track real activity in economies such as the United States, the euro area, or its individual member countries are—if available at all—released only with a long lag, at a quarterly frequency, and/or with very short histories. Still, if one considers all the economic series that are available, it is possible to construct quite a large data set. While each individual indicator of this data set may not look too informative on its own, the data set as a whole looks quite promising, as it features indicators on all important aspects of the Swiss economy.

In this paper, we compare several methods for tracking current economic conditions in Switzerland using this large data set. The two common features of the methods is that they are able to handle (i) large data sets and (ii) indicators with different frequencies. They can therefore be characterized as large-scale mixed-frequency methods. The study relates to similar investigations that have been performed for other countries. Evans (2005), Giannone, Reichlin, and Small (2008), Bańbura, Giannone, and Reichlin (2011), Bańbura and Rünstler (2011), and Kuzin, Marcellina, and Schumacher (2011) are some prominent examples.

We consider three approaches: information combination, model combination, and variable selection. For *information combination*, we rely on factor model techniques.[1] Such models assume that a small number of factors can be used to describe the fluctuations in a

[1] Large Bayesian VARs would be an alternative, but so far they have only been used with single frequencies, and adapting them to the use of mixed frequencies would create computational challenges.

given data set and that those factors are highly correlated with the business cycle and GDP (see, e.g., Stock and Watson 2002, 2011). In this study, we concentrate on a large-scale dynamic factor model (DFM), which is based on the Kalman filter and is estimated by the expectation–maximization (EM) algorithm. This is the current state-of-the-art model for nowcasting purposes (see Bańbura, Giannone, and Reichlin 2011, Doz, Giannone, and Reichlin 2012, and Bańbura and Modugno 2014). The second approach uses *model combination*, i.e., it combines forecasts from different models. In our case, single-indicator models are used to explain GDP within a linear regression framework. For higher-frequency variables (weekly and monthly indicators), mixed-data sampling (MIDAS) is used to take into account the temporal aggregation issue. The third approach is *variable selection*. In this case, we employ a variable selection technique based on a specific-to-general methodology that can handle large data sets and mixed-frequency settings. As benchmark models, we consider univariate time-series models as well as popular Swiss leading indicators such as the PMI and the KOF economic barometer.

To compare the models under investigation and their benchmarks, we conduct a pseudo-out-of-sample forecast exercise. Using our large data set of more than 600 variables at weekly, monthly, and quarterly frequency, and taking into account two different states of information, we generate forecasts from the different models for the period 2005:Q1–2015:Q2.[2] With all our approaches, we take into account the problem of missing observations at the end of the sample (ragged-edge problem). We compare the forecasting performances by means of root mean squared forecast errors (RMSEs) and investigate their ranking over time by looking at different subperiods and rolling windows. Besides RMSEs, we investigate the models' ability to forecast business cycle phases.

Our results show that all three approaches using the large data set clearly beat relevant benchmarks such as univariate time-series models and the popular single-indicator models using the PMI or the KOF economic barometer. The factor model performs best for

[2]The reason for not having a longer evaluation sample is that for the case of Switzerland, many economic indicators start only in 1990 or even later, which automatically limits the estimation sample of the models to some extent.

the total evaluation sample. Model combination also performs well, but it does not capture the financial crisis period very well. After the crisis, model combination slightly outperforms the factor model, particularly for the two-step-ahead forecast. Variable selection performs well on average for the one-step-ahead forecast but loses ground when forecasting two steps ahead. Finally, we show that a pooling (simple average) of the models under consideration produces even better results than the best single-model procedure.

2. Data

To understand the choice of forecasting approaches that we evaluate, some background on the Swiss data situation is warranted. An economist who wants to monitor current activity in Switzerland faces a data situation that is worse than what one may expect given Switzerland's high per-capita income: many indicators that are routinely used to monitor real activity in economies such as the United States and the euro area are released with a considerable lag, are available only at a quarterly frequency, and/or have short histories.

A prominent example that illustrates all three issues is the industrial production, turnover, and new orders release: its publication lag is about two months after the end of the quarter. Moreover, while the time series are available at a monthly frequency, the values for all three months of the quarter are released at once. Finally, the monthly series only go back to 2011, illustrating the problem of short histories; the quarterly series go further back.

Another example of a long publication lag and a quarterly frequency is the job statistics (the equivalent to the firm survey part of the United States' monthly employment situation release), which is published about two months after the end of the quarter. Moreover, it is only available at a quarterly frequency. Other important data releases that are only available at a quarterly frequency include construction activity, wages, and consumer confidence.

A prominent example of a short history is certainly the quarterly labor force survey (the equivalent to the household survey part of the United States' employment situation release) that only goes back to 2010. Still, there exist indicators with short publication lags and monthly frequency. However, they are often quite noisy and/or not too strongly connected with GDP. Examples are merchandise exports and imports, financial markets data, and foreign activity indicators.

In light of this data situation, we think it makes sense to use all available information[3] and construct an as large as possible data set that includes both quarterly and monthly indicators. This novel data set for the Swiss economy consists of 627 variables (361 monthly, 266 quarterly) covering seventeen areas. All data are used in calendar-adjusted, seasonally adjusted, and outlier-adjusted terms.[4] Details of the data set are shown in table 1. In principle, the data set starts in 1975. However, many indicators start only in 1990 or even later, which automatically limits the estimation period to some extent. One important aspect of this data set is the large fraction of quarterly data. Around one-third of variables are observed only in quarterly frequency. This is very atypical compared with similar studies for other countries that only use a very limited number of quarterly variables (GDP and possibly some quarterly surveys).

3. Forecasting Approaches

In light of the Swiss data situation and the choice of data set outlined in the previous section, the forecasting approaches under consideration need to be able to handle a large data set with different publication lags and frequencies. We evaluate three approaches: an *information combination* approach based on a DFM, a *model combination* approach pooling single-indicator models, and a specific-to-general *variable selection* procedure. In the following we briefly outline these three approaches. An online appendix (available at http://www.ijcb.org) provides more details on the models.

3.1 Information Combination Using a Dynamic Factor Model

The dynamic factor model approach models the co-movements of a panel of observed time series, x_t, as driven by a small number of latent factors, f_t, and idiosyncratic components, u_t, which can be represented as

[3]We checked if this intuition holds up by using two smaller indicator sets in our best-performing model (the dynamic factor model). See section 4.

[4]Indicators that are not available on a seasonally adjusted basis were calendar adjusted, seasonally adjusted, and outlier adjusted using the X-13ARIMA-SEATS procedure.

Table 1. Large-Scale Data Set for the Swiss Economy

Area	Soft Data		Hard Data		Prominent Examples
	M	Q	M	Q	
GDP				27	Total GDP, demand components, value added of sectors.
Labor Market	1	4	42	42	OASI statistics, unemployment statistics, job statistics, employment statistics, surveys, hours worked, wage index.
Consumption	4	13	6		Overnight stays of domestic visitors, retail sales, import of fuel, electricity consumption, new car registrations, consumer sentiment.
Investment			3	11	SwissMEM survey, imports of investment goods, industrial production of investment goods.
Foreign Trade			19	2	Trade statistics, overnight stays of foreign visitors.
International Activity	24	13	39	8	Several indicators covering Germany, euro area, United States, Japan, emerging Asia, and the CESifo world economic survey.
Financial Markets			64		Stock market indexes, exchange rates, commodity indexes, monetary aggregates, monetary conditions, interest rates, spreads.
Prices			12	3	Consumer prices, real estate prices, import prices, production prices, construction prices.
Construction Sector	15	3	6	21	Surveys, production, order books, cement deliveries.
Retail Trade Sector	6	5			Surveys.
Wholesale Trade Sector		14			Surveys.
Accommodation Sector		18	1		Overnight stays, surveys.
Manufacturing Sector	51	41	2	1	Industrial production, surveys, PMI, electricity production, number of working days.
Project Engineering Sector	8	7			Surveys.
Banking Sector	20	22	14		Credit statistics, surveys, balance sheet statistics, illiquidity index.
Insurance Sector	16	9			Surveys.
Other	7	2	1		Surveys.

$$x_t = \lambda f_t + u_t, \tag{1}$$

where f_t is an $r \times 1$ vector of common factors and λf_t is the common component. For the factors, we assume that they follow a finite-order Gaussian VAR,

$$f_t = \Phi_1 f_{t-1} + \cdots + \Phi_p f_{t-p} + v_t. \tag{2}$$

Both sets of equations constitute a state-space system. Doz, Giannone, and Reichlin (2012) show that the parameters and the latent factors can be estimated by maximum likelihood (ML) using the EM algorithm, which is a consistent estimator. Using the Kalman smoother in combination with the EM algorithm dominates principal components and two-step estimates.

Since the data set contains a large number of quarterly indicators, we use the modification suggested by Bańbura and Modugno (2014) allowing for mixed frequencies and arbitrary patterns of missing data. x_t is measured in monthly frequency (quarterly variables are treated as unobserved during the first two months of the quarter) and non-stationary variables are included as three-month growth rates.[5] Our baseline model uses two factors ($r = 2$) and one lag in the VAR of the factors ($p = 1$).[6,7]

[5]Giannone, Reichlin, and Small (2008), Angelini et al. (2011), and Bańbura and Rünstler (2011) also use three-month growth rates, whereas for example Bańbura and Modugno (2014) follow Mariano and Murasawa (2003) and stationarize trending monthly variables using month-on-month growth rates. We also evaluated the model using this transformation but found that the stationarization using three-month growth rates performs consistently better (see the online appendix).

[6]In choosing the number of factors, we try to obtain as parsimonious as possible a specification. While the inclusion of a second factor leads to a substantial increase in the correlation between GDP and its in-sample fit, a third and fourth factor do not lead to notable gains. As a robustness check, we estimated factor models using one and three factors and computed corresponding forecasts in the out-of-sample experiment. Although all findings of the baseline specification survived, two factors provide the best overall performance. The lag length in the VAR has no impact on the nowcasting performance and only very limited effects for the forecast. We therefore choose the most parsimonious specification, i.e., two factors and one lag.

[7]A different version of this model with four factors and estimated by the two-step procedure is proposed in Galli (2018) to obtain a business cycle index for the Swiss economy.

3.2 Model Combination Using MIDAS Regressions

This forecast approach pools the forecasts of several single-indicator models to obtain a final forecast. We first describe the single-indicator models and then present the combination method.

The single-indicator models relate h-steps-ahead GDP growth to the last p observations of the indicator using MIDAS and ARDL (autoregressive distributed lag) models,[8]

$$y^q_{t^q+h} = \begin{cases} \mu + \sum_{k=0}^{p^q} \beta_{k+1} x^q_{t^q+h-J-k} + u_{t^q+h} \\ \qquad\qquad \text{for quarterly indicators} \\ \mu + \sum_{k=0}^{p^m} \omega_k(\theta) x^m_{t^q+h,N^m-J-k} + u_{t^q+h} \\ \qquad\qquad \text{for monthly indicators} \\ \mu + \sum_{k=0}^{p^w} \omega_k(\theta) x^w_{t^q+h,N^w-J-k} + u_{t^q+h} \\ \qquad\qquad \text{for weekly indicators,} \end{cases} \tag{3}$$

where x denotes the indicator, which is available in quarterly (x^q), monthly (x^m) or weekly frequency (x^w). To allow for the most flexible dynamic specification, non-stationary variables are included as previous-period growth rates (stationary variables enter in levels).

For the quarterly frequency, the model is simply a distributed lag model of the indicator which is estimated by OLS without any restrictions. For the indicators available in monthly frequency, $N^m - J - k$ denotes the monthly lag of a specific indicator and $N^m = 3$ in this case (three monthly observations per quarter). J indicates the number of missing observations (in terms of months) for a specific quarter. k is measured in terms of months. For instance, when all monthly information for a given quarter is available, the forecasting horizon is $h = 1$, and six months (two quarters) are considered as lags, $k = 5$, $J = 0$, and $x^m_{t^q+1,3}, x^m_{t^q+1,2}, x^m_{t^q+1,1}, x^m_{t^q+1,0}, x^m_{t^q+1,-1}, x^m_{t^q+1,-2}$ are used as regressors in the model. This implies using six lags of monthly observations or a full set of information for quarter $t^q + 1$ and t^q.

[8]In a previous version of the paper, we allowed for lagged endogenous terms. However, this led to inferior forecasting results. Therefore, we opted for the simpler specification.

For weekly observations the same reasoning applies, although N^w is larger than N^m and time varying. Consequently, p^w is allowed to be larger than for quarterly and monthly indicators and J now measures the number of missings weeks of the respective quarter. The maximum lags for p^q, p^m, and p^w are set to match roughly one year of information; therefore, $p^q_{max} = 4$, $p^m_{max} = 12$, and $p^w_{max} = 48$.

For the higher-frequency indicators (monthly and weekly frequency) an Almon distributed lag model (Heinisch and Scheufele 2018) is applied. The function $\omega_k(\theta)$ is given by

$$\omega^i_k(\theta) = \omega^i_k(\theta_0, \theta_1, \dots \theta_q) = \theta_0 + \theta_1 k + \theta_2 k^2 + \cdots + \theta_q k^q. \qquad (4)$$

In this case the model can be estimated by restricted least squares. Even with a polynomial degree q that is substantially smaller than p, many functional forms can be well approximated. For each indicator, q together with p is selected by Bayesian information criterion (BIC) at each forecasting round (following Heinisch and Scheufele 2018).

To obtain the final forecast, we then pool the individual forecasts of each indicator: we take the average of all models with a BIC smaller than the one of the optimal AR model (GDP regressed on a constant and its own lags, where the number of lags is chosen by BIC).

3.3 Variable Selection Using a Specific-to-General Approach

A well-known alternative to information combination or model combination is variable selection. First, based on certain criteria, specific indicators from the large panel of indicators are selected. In a next step, they are then used in single equations. Typical examples are step-wise procedures that add (specific-to-general) or eliminate (general-to-specific) variables from a specification by means of information criteria or statistical tests (see, e.g., Ng 2013). Recent examples include Castle, Doornik, and Hendry (2011) and Chudik, Kapetanios, and Pesaran (2016).

We use a modified version of the specific-to-general approach suggested by Herwartz (2011a, 2011b): when selecting the variables we correct the significance levels for multiple testing similar to Chudik, Kapetanios, and Pesaran (2016). Moreover, we apply blocking (see, e.g., McCracken, Owyang, and Sekhposyan 2015) and realignment to allow for mixed frequencies and different publication lags. The algorithm works as follows:

(i) The blocking and realignment yields a balanced quarterly panel of candidate indicators, W (non-stationary variables enter in terms of period-wise growth rates). The set of selected indicators, W^{sg}, is initialized with only a constant.

(ii) Project GDP growth onto W^{sg} and retain the estimated residuals $\hat{u}$.

(iii) Separately regress $\hat{u}$ on each candidate indicator in W. For each regression, calculate the Lagrange multiplier (LM) statistic.

(iv) If the highest LM statistic is above the critical value computed according to the Benjamini and Hochberg (1995) procedure that controls for multiple testing, move the corresponding indicator from W to W^{sg} and return to step (ii). Otherwise proceed to step (v).

(v) Use the last iteration's step (ii) projection to generate the final GDP forecast.

3.4 Benchmark Models

As benchmark models, we consider (i) optimal AR models and (ii) popular leading indicators. The AR model has a maximum of four lags, with the lag length being optimized at each forecast round using the BIC. For the leading-indicator models, we consider the two most prominent leading indicators for the Swiss economy: the PMI in the manufacturing sector and the KOF economic barometer. Both indicators are released on a monthly basis, receive some attention in the public, and are promising in terms of forecasting performance (see, e.g., Maurer and Zeller 2009, Lahiri and Monokroussos 2013, and Abberger et al. 2014). For the two leading indicators, we use the same MIDAS framework as outlined in section 3.2, where the specification is selected using BIC. Both the AR and the leading-indicator models are optimized separately for each forecast horizon.

4. Model and Forecast Evaluation

To evaluate the models, we produce a one- and two-quarter-ahead forecast using a recursive pseudo-real-time setup.[9] The different models are compared in terms of root mean squared error (RMSE). The target variable is the annualized quarter-on-quarter growth of Swiss GDP (real, calendar, and seasonally adjusted).

Two specific dates are selected to time the forecast production. The first, “early-quarter,” information set is given by indicator information available on the 11th of March/June/September/December. At this date, surveys are usually available for one month of the nowcast quarter, hard data for one month or not at all, and financial data for two months.[10] For this information set, we use an underlying data vintage available on September 11, 2015.

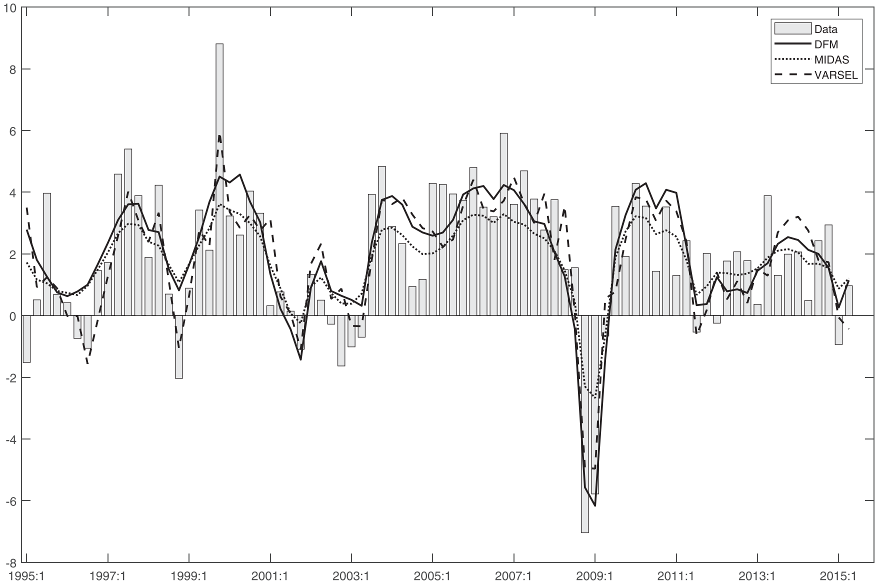
The second, “late-quarter,” information set is given by data available on the 6th of May/August/November/February. At this date, surveys are usually available for all three months of the nowcast quarter, hard data for two or three months, and financial data for all three months. Theoretically, this additional information should improve the forecasts. For this information set, we use an underlying data vintage available on November 6, 2015.

The evaluation is conducted over the period 2005:Q1–2015:Q2. It is based on GDP data that came with the State Secretariat for Economic Affairs’ official GDP release for the second quarter of 2015. In what follows, the forecast horizon will always be defined relative to the GDP data situation. This means that if, e.g., GDP is available up to Q4, the one-step-ahead forecast (i.e., the nowcast, defined as $h = 1$) will—for both information sets (March 11 and May 6)—target Q1 GDP growth and the two-step-ahead forecast ($h = 2$) Q2 GDP growth.

[9]Note that such a pseudo-real-time setup does not take into account the fact that, in reality, indicators may be subject to revisions, including revisions stemming from the seasonal adjustment procedure.

[10]Kaufman and Scheufele (2017) investigate the informational content of the surveys by the KOF Swiss Economic Institute—one of the main sources for business tendency data on Switzerland. They find that these surveys are helpful for explaining inflation, employment growth, and the output gap, but less so for GDP growth.

Figure 1. In-Sample Fit of the Three Approaches under Investigation



Note: This graph shows the in-sample explanatory power of three models along with quarterly annualized GDP growth.

4.1 In-Sample Fit

Figure 1 plots the in-sample fit of the three approaches under investigation against realized GDP growth.[11] Several observations are in order. First, the models' general interpretations of the business cycle are similar: all models identify phases of weakness around 1996, 1999, 2002, and 2009. Also, the models agree that there were significant decelerations during 2011 (strong CHF appreciation and a global slowdown) and at the beginning of 2015 (strong CHF appreciation following the end of the EUR–CHF exchange rate floor). Second, the

[11]While the computation of the DFM in-sample fit is straightforward, it is less obvious how to compute it based on MIDAS and VARSEL, because these are direct forecasting approaches. For MIDAS and VARSEL we therefore estimate the indicator models using a balanced data set. This implies that for a given quarter of GDP we take all three months of indicator information as given.

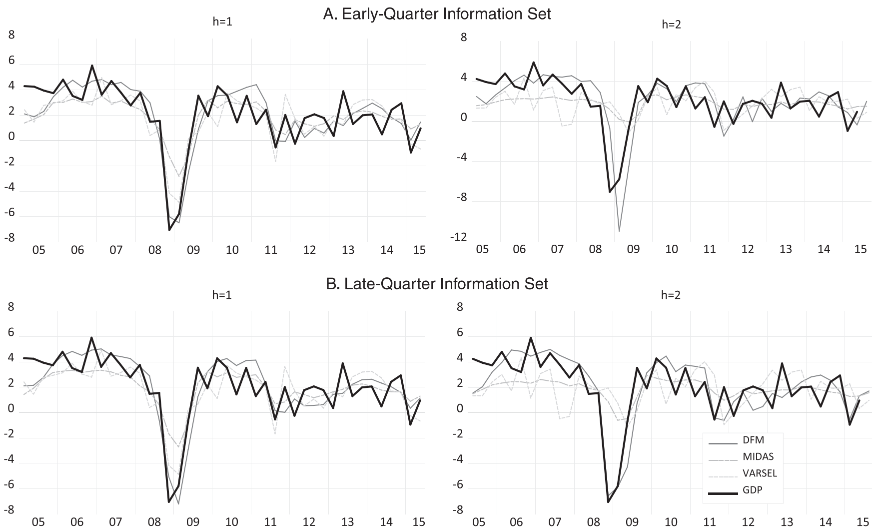
models also agree on a number of quarters, where GDP appears to be driven by idiosyncrasies that are not mirrored in the broad data set from which the model dynamics are constructed. Examples are the strong GDP growth rates of 1995:Q1, 1999:Q3, and 2014:Q4 and the weak GDP growth in 2004:Q3 and 2004:Q4, 2010:Q3, 2011:Q1, and 2014:Q2. This illustrates the usefulness of a large data set for measuring the underlying business cycle dynamics in a broader sense than what is captured by GDP. Third, the smoothness of the in-sample fit varies considerably, with the model combination approach (MIDAS) being particularly smooth (standard deviation of 1.3). The other two models—the dynamic factor model (DFM) and the variable selection approach (VARSEL)—produce a more volatile fit, with standard deviations of approximately 1.9. For comparison, the standard deviation of GDP is 2.4 percentage points. Fourth, the in-sample fit varies only slightly across models. MIDAS has an in-sample R^2 of 0.71. The two other models' R^2 are 0.63 (VARSEL) and 0.65 (DFM). Whether these good in-sample fits translate into a good forecasting performance will be addressed in the next section.

4.2 Out-of-Sample Evaluation Results

Figure 2 plots the forecasts of the three approaches under investigation over time. The main features of the models are directly visible in these graphs. For the nowcast ($h = 1$), all of the investigated models more or less follow the tendency of GDP growth. Clearly, there are periods where the connection is stronger (e.g., before, during, and after the financial crisis) and periods where GDP growth deviates more persistently from the predictions of the models (in 2005 and 2013). This broadly corresponds to the in-sample results. Generally, forecasts of the different models are highly correlated (particularly for $h = 1$). Additionally, forecasts using the early-quarter information set are not much different from the late-quarter information set. As expected, the forecasts are more accurate for the nowcast ($h = 1$) than for the following quarter ($h = 2$).

Looking at the different models, we see that the DFM captures the financial crisis period 2008/09 very well. The model combination strategy (MIDAS) is less successful during the crisis than the DFM, but at least gets the tendency right. It generally delivers less volatile forecasts and is therefore less flexible in situations of rapid

Figure 2. Model Forecasts and Realizations



Notes: The graphs show the recursively computed annualized GDP forecasts of different models for two forecasting horizons (h = 1 and h = 2) and realized GDP growth. Panel A is based on the early-quarter information set and panel B is based on the late-quarter information set.

change. The variable selection approach also performs quite well for the nowcast ($h = 1$) during the crisis period. However, this forecasting method is very volatile for $h = 2$ and seems to be less correlated with GDP growth than most of the other forecasting models.

4.2.1 Average Performance

Table 2 reports the relative root mean squared errors of the models against the AR benchmark. Although the forecast errors for the post-crisis sample—which covers 2010:Q1–2015:Q2—are, on average, smaller (see, e.g., the AR benchmark) in absolute terms, the relative performance of the models under investigation has deteriorated somewhat (relative to the AR benchmark). A similar result is well documented for the pre-crisis period relative to the crisis period (Drechsel and Scheufele 2012; Kuzin, Marcellino, and Schumacher 2013).

Table 2. Relative RMSEs of Different Forecasting Methods

	Total Sample 2005:Q1–2015:Q2		Post-Crisis Sample 2010:Q1–2015:Q2	
	$h = 1$	$h = 2$	$h = 1$	$h = 2$
AR Benchmark	2.1689	2.5081	1.6334	1.2686
A. Early-Quarter Information				
a. Information Combination				
DFM	0.666*	0.806*	0.909	1.221
b. Model Combination				
MIDAS	0.768**	0.870**	0.760***	0.927
c. Variable Selection				
VARSEL	0.726*	1.056	0.936	1.470
d. Leading Indicator Models				
PMI	0.829	0.871*	1.001	1.055
KOF Barometer	0.850	0.844	0.923	0.958
e. Pooling of Different Procedures				
COMBO1	0.654**	0.701**	0.809**	0.999
COMBO2	0.641**	0.782*	0.785**	1.112
COMBO3	0.630*	0.792*	0.838*	1.261
COMBO4	0.700**	0.942	0.776**	1.149
B. Late-Quarter Information				
a. Information Combination				
DFM	0.656*	0.588*	0.833*	1.114
b. Model Combination				
MIDAS	0.719**	0.818**	0.704***	0.922
c. Variable Selection				
VARSEL	0.726*	1.059	0.937	1.486
d. Leading Indicator Models				
PMI	0.733*	0.845	0.899	1.359
KOF Barometer	0.938	0.834	1.029	1.057

(*continued*)

Table 2. (Continued)

	Total Sample 2005:Q1–2015:Q2		**Post-Crisis Sample 2010:Q1–2015:Q2**	
	$h = 1$	$h = 2$	$h = 1$	$h = 2$
e. Pooling of Different Procedures				
COMBO1	0.619**	0.588**	0.741***	0.930
COMBO2	0.615**	0.711**	0.741***	1.039
COMBO3	0.617**	0.695*	0.797**	1.143
COMBO4	0.676**	0.918	0.753***	1.153

Notes: The table shows relative root mean squared errors (RMSEs) for $h = 1$ (nowcast) and $h = 2$ (one additional quarter ahead) using two different states of information. Besides the benchmark AR model, all numbers are defined relative to the benchmark. Pooling of different procedures includes the following models using equal weights. COMBO1: DFM + MIDAS, COMBO2: DFM + MIDAS + VARSEL, COMBO3: DFM + VARSEL, COMBO4: MIDAS + VARSEL. ***, **, and * indicate whether a model's predictive ability (using the DM test) is significantly better than the benchmark (at the 1 percent, 5 percent, and 10 percent level, respectively).

Overall, the DFM performs best in the total evaluation sample. The forecast gains against the AR benchmark models are more than 30 percent. Compared with the leading-indicator models, the DFM offers improvements between 10 and 20 percent. In the post-crisis sample, the gains relative to the AR decline to 10–20 percent. The improvements in forecasting accuracy from the early-quarter to the late-quarter information set are, on average, small. The gains from the early to the late information set are only 1 percent and 5 percent, for the DFM and MIDAS, respectively. For $h = 2$, the gains are slightly larger.

Among the approaches under investigation, the forecast gains of the DFM against MIDAS and VARSEL are around 10 percent for $h = 1$ (see table 3 for pairwise model comparisons). None of the three models is able to systematically outperform the other two approaches. When considering the pooling of different methods (COMBO1 and COMBO2), we find that those are on average often better than the individual procedures and do significantly outperform the variable selection procedure (VARSEL). For $h = 2$, VARSEL performs very poorly compared with the other two produres and the pooling of methods.

Table 3. Pairwise Forecast Comparisons

Bench	$h = 1$				$h = 2$			
	DFM	**MIDAS**	**VARSEL**	**COMBO1**	**DFM**	**MIDAS**	**VARSEL**	**COMBO1**
A. Early-Quarter Information								
MIDAS	1.15				1.08			
VARSEL	1.09	0.94			1.31***	1.21***		
COMBO1	0.98	0.85	0.90		0.87	0.81	0.66***	
COMBO2	0.96	0.83	0.88**	0.98	0.97	0.90	0.74***	1.11***
Best Model (in % of time)	35.7	45.2	19.1	4.8	41.5	22.0	17.1	19.5
B. Late-Quarter Information								
MIDAS	1.10				1.39			
VARSEL	1.11	1.01			1.80**	1.29***		
COMBO1	0.94	0.86	0.85*		1.00	0.72	0.56**	
COMBO2	0.94	0.86	0.85***	0.99	1.21	0.87	0.67***	1.21**
Best Model (in % of time)	31.0	38.1	14.3	9.5	36.6	31.7	14.6	14.6

Notes: Results of pairwise comparisons are displayed using relative RMSEs and the test for equal predictive ability of DM. The benchmark is given by the top line (and is used as the denominator of the relative RMSE). ***, **, and * indicate whether the DM test is significant at the 1 percent, 5 percent, and 10 percent level, respectively. Additionally, we show the percentage of times when models provide the best forecast.

Interestingly, when the focus is not on the average performance in terms of RMSEs, but on picking the best model as often as possible (best model in percentage of time; see table 3), the ranking of models changes. For $h = 1$, MIDAS is most often the model that is closest to the realizations, followed by the DFM. For $h = 2$, the order is turned around, with DFM slightly more successful. Pooling of different methods is not successful in this case.

The forecasting performance of model combination based on MIDAS models is slightly less accurate for the total sample compared with the DFM. The forecasting gains in terms of RMSEs are approximately 23 percent (early-quarter information) and 28 percent (late-quarter information). This is broadly in line with previous research that compares similar methods (Bańbura et al. 2013; Kuzin, Marcellino, and Schumacher 2013; Foroni and Marcellino 2014). However, for the post-crisis sample and $h = 1$, model combination based on MIDAS models offers the largest and most significant improvement relative to the benchmark model.

Interestingly, the specific-to-general variable selection approach (VARSEL) performs reasonably well for the nowcast period (and is able to outperform the benchmark for the total sample). For one quarter ahead ($h = 2$), however, this approach is not very reliable, and for the post-crisis sample there are no significant improvements relative to the benchmark.

It is also instructive to assess how three approaches under investigation compare with single-leading-indicator models. For the total sample, the performance of the PMI and KOF economic barometer is less accurate than the DFM and slightly inferior to the model combination and variable selection approaches. Only the PMI offers some significant improvements relative to the benchmark. The performances of the two leading-indicator models have clearly deteriorated in the post-crisis period, and the models contain only little information. Most interestingly, the KOF economic barometer—which is itself calculated from a large-scale factor model—does not outperform the much simpler PMI.

4.2.2 Varying the Size of the Data Set

The fact that we use a very large data set seems to be controversial. Boivin and Ng (2006) for the United States and Caggiano,

Table 4. Relative RMSEs of DFMs Using a Smaller Data Set

	Early-Quarter Information Set		Late-Quarter Information Set	
	$h = 1$	$h = 2$	$h = 1$	$h = 2$
Baseline	0.666	0.806	0.656	0.588
113 Indicators	0.719	0.809	0.682	0.722
20 Indicators	0.733	1.037	0.705	0.877

Notes: The table shows relative root mean squared errors (RMSEs) against the AR benchmark for $h = 1$ (nowcast) and $h = 2$ (one additional quarter ahead) using two different states of information. "Baseline" corresponds to the model considered above; "113 Indicators" and "20 Indicators" use smaller data sets.

Kapetanios, and Labhard (2011) for some euro-area countries show that including a very large set of variables in the factor model might lead to inferior forecasting results. Moreover, Bańbura, Giannone, and Reichlin (2011) and Bańbura and Modugno (2014) find that including disaggregate information does not lead to an improved forecasting performance for euro-area GDP forecasts.

Therefore, we compare the best-performing model (the DFM estimated with the EM algorithm) using the large data set with DFMs using a medium-sized and a smaller data set. The smaller data set contains twenty variables that were selected using expert judgment, whereas the medium-sized data set contains 113 indicators that were selected as follows: we started with our large data set and went through each of the indicator categories outlined in table 1 of the paper. For categories with more than ten monthly indicators, we deleted the quarterly indicators and some details of the monthly indicators. For categories with less than ten monthly indicators, we deleted details of the quarterly indicators. The goal was the get about five to ten indicators per category.

Table 4 reports the results. The empirical performance of the medium-sized data set is lower than that of the large data set, although the differences are not very large and also the medium-sized data set still clearly beats all benchmarks. The smaller data set performs clearly worse than the large data set and also worse than the medium-sized data set.

The fact that more indicators appear to be better for Switzerland is most likely driven by the relatively unsatisfactory data situation in Switzerland, which we describe in section 2: many indicators that economists routinely use to track economic developments in the United States (or also in the euro zone) are simply not available for Switzerland or, if they are, they are only available on a quarterly frequency, with a long publication lag and/or a short history. Therefore, it seems to be a good strategy to use whatever is available and go with a large data set.

4.2.3 Time-Varying Forecasting Performance

Figure 3 gives a more complete picture of the time-varying performance of the models. First, it confirms that the good performance of the factor model mainly comes from the crisis period 2008/09. Second, it shows that the performance of the three approaches under investigation relative to the AR benchmark has deteriorated in 2010–13. Third, most recently, the models' performance gained again, most likely due to the exchange rate shock in 2015. Interestingly, the performance of the model combination approach based on MIDAS models remains very stable over time and is less sensitive.

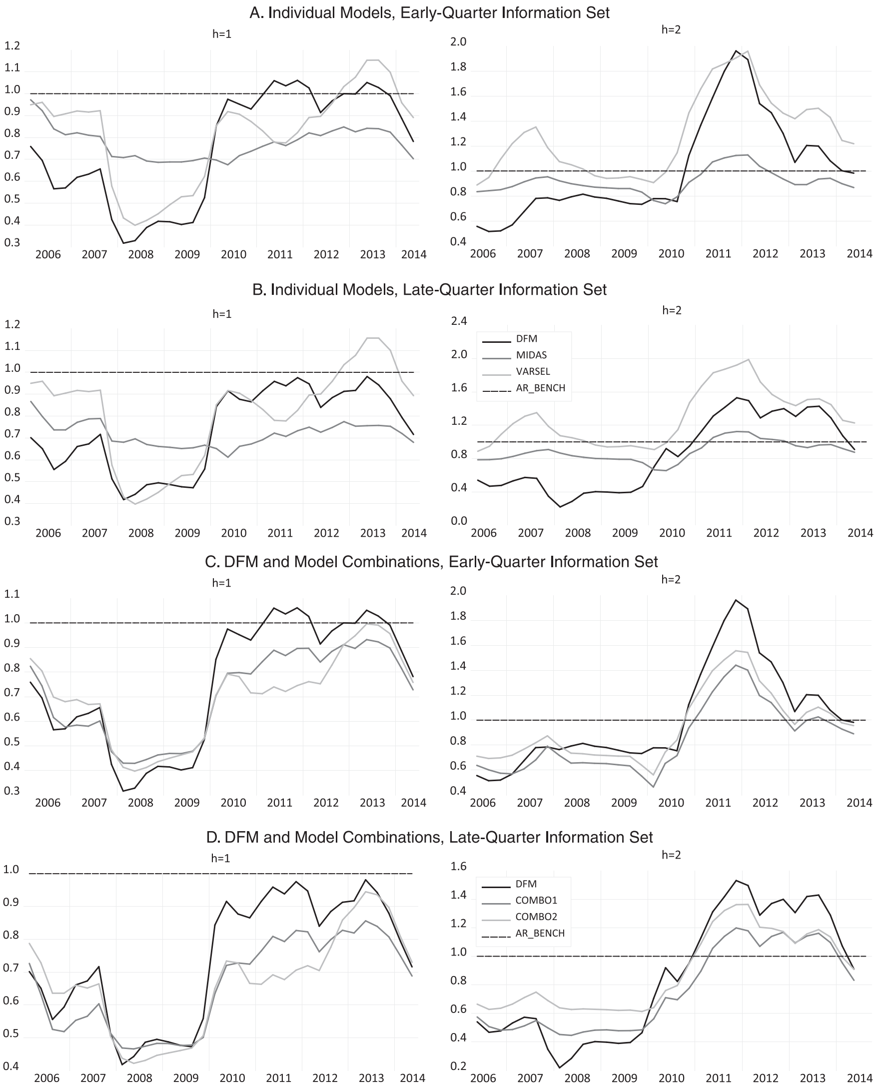
4.2.4 Pooling Different Forecasting Models

Table 2 and figure 3 show that one may obtain additional gains in average performance and in terms of reliability (significance) when pooling different forecast methods. For the total sample and the nowcast period, just pooling the DFM and MIDAS (COMBO1) results in a very good performance. In some cases, pooling all three methods (COMBO2) improves the results even further. Generally, the different poolings perform very similarly, and it is difficult to identify a clear winner. Pooling of mixed-frequency model forecasts is stable and reliable in terms of forecast accuracy. Additionally, figure 3 shows that, since 2010, the pooling of different procedures is superior to the single DFM approach.

4.2.5 Forecasting the Tendency of Output Growth

When looking at other measures of forecasting performance, our general results hold. However, the details may be slightly different. By

Figure 3. Rolling Relative RMSEs (Two-Year Windows)



Notes: The graphs show eight quarters centered moving average of a model's RMSE relative to the AR benchmark model. Values smaller than one indicate that the local forecasting performance is better than the benchmark model.

looking at whether the models are able to accurately capture the general tendency of output growth, we go from a continuous measure (in our case, the RMSE), to a nominal measure. In practice, the forecaster may not be judged by the specific distance of the forecast to a target, but by whether he got the general tendency right. By using a trichotomous measure, we take into account three different phases: low, moderate, and strong growth states. We can then investigate how our forecasts match those categories when compared with the realizations. Our definition of the three different phases is motivated by two different considerations: first, by the empirical distribution of GDP growth since the 1990s, and second, by policy considerations. A policymaker may be interested in whether the economy expands robustly, which we define by growth that is markedly greater than the long-term average of 1.6 percent—so we opt for the 2 percent threshold. Additionally, a policymaker might become worried when growth is only marginally positive or even negative. This motivates our second threshold of 0.5 percent.

Table 5 shows the main results for the nowcast period. Generally, the main findings are compatible with previous results. First, the differences among the different approaches tend to be small. Second, all models under investigation are informative. Thus, the null hypothesis of independence between forecasts and realizations can be rejected in all cases. On average, the predictions match the corresponding realized categories in approximately 52–64 percent of the cases. Third, there seems to be only a very small improvement in terms of accuracy from the early to the late information set. Fourth, model averaging does not improve the performance. Overall, the DFM provides the best results in terms of predicting the business cycle phase (correlation coefficient).

5. Conclusions

Monitoring economic developments in real time is one of the most important but also most challenging tasks that the applied economist working on Switzerland faces. In this paper, we set up a large database containing hundreds of potentially relevant variables. We then considered different approaches to condensing the information of the data set into a GDP forecast. The traditional approaches often used in practice select one or a few indicators based on expert

Table 5. Contingency Tables for Business Cycle Phase Predictions

A. Early-Quarter Information Set						
	a. DFM			**b. MIDAS**		
	Realization			**Realization**		
	(−∞, 0.5]	**(0.5, 2]**	**(2, +∞)**	**(−∞, 0.5]**	**(0.5, 2]**	**(2, +∞)**
Prediction						
(−∞, 0.5]	11.9	4.8	2.4	7.1	0.0	2.4
(0.5, 2]	4.8	4.8	14.3	9.5	11.9	16.7
(2, +∞)	2.4	14.3	40.5	2.4	11.9	38.1
% of Correct Predictions			57.14			57.14
Correlation Coefficient			0.59			0.55
Pearson χ^2			14.40			12.80
p Value			0.006			0.012
	d. VARSEL			**e. COMBO1**		
	Realization			**Realization**		
	(−∞, 0.5]	**(0.5, 2]**	**(2, +∞)**	**(−∞, 0.5]**	**(0.5, 2]**	**(2, +∞)**
Prediction						
(−∞, 0.5]	11.9	7.1	0.0	11.9	2.4	2.4
(0.5, 2]	4.8	4.8	16.7	4.8	7.1	16.7
(2, +∞)	2.4	11.9	40.5	2.4	14.3	38.1
% of Correct Predictions			57.14			57.14
Correlation Coefficient			0.64			0.61
Pearson χ^2			17.15			15.93
p Value			0.002			0.003
B. Late-Quarter Information Set						
	a. DFM			**b. MIDAS**		
	Realization			**Realization**		
	(−∞, 0.5]	**(0.5, 2]**	**(2, +∞)**	**(−∞, 0.5]**	**(0.5, 2]**	**(2, +∞)**
Prediction						
(−∞, 0.5]	11.9	4.8	2.4	7.1	2.4	2.4
(0.5, 2]	4.8	7.1	9.5	11.9	7.1	16.7
(2, +∞)	2.4	11.9	45.2	0.0	14.3	38.1
% of Correct Predictions			64.29			52.38
Correlation Coefficient			0.65			0.55
Pearson χ^2			17.56			12.86
p Value			0.002			0.012

(*continued*)

Table 5. (Continued)

B. Late-Quarter Information Set						
	d. VARSEL			**e. COMBO1**		
	Realization			**Realization**		
	($-\infty$, 0.5]	**(0.5, 2]**	**(2, $+\infty$)**	**($-\infty$, 0.5]**	**(0.5, 2]**	**(2, $+\infty$)**
Prediction						
($-\infty$, 0.5]	11.9	7.1	0.0	9.5	2.4	2.4
(0.5, 2]	4.8	4.8	16.7	7.1	7.1	14.3
(2, $+\infty$)	2.4	11.9	40.5	2.4	14.3	40.5
% of Correct Predictions			57.14			57.14
Correlation Coefficient			0.64			0.55
Pearson χ^2			17.15			12.92
p Value			0.002			0.012

Notes: Results of pairwise comparisons about three different business cycle phases. The numbers reflect frequencies (in percentage points) how predictions match with realizations. 1: low/negative growth (below 0.5 percent), 2: moderate growth (0.5–2 percent), and 3: high growth (above 2 percent). Additionally, statistics about the degree of association are displayed (as well as a test of independence).

knowledge and derive the forecast using OLS regressions or a small-scale dynamic factor model. Alternatively, one may use all indicators without an expert's pre-selection. We presented and compared three approaches to doing so.

The first approach, factor-based *information combination*, extracts a small number of common factors from the database and forms GDP forecasts based on these factors. It is implemented by a Kalman-filter-based DFM approach which is estimated by the EM algorithm. This method provides very good results for nowcasting GDP and beats relevant benchmarks such as univariate time-series models, prominent leading-indicator models, and a small-scale factor model.

The second approach, *model combination*, performs estimations based on MIDAS equations for each indicator and then combines the resulting forecasts to form a final GDP forecast. This makes communicating a particular indicator's contribution to the forecast very easy. Also, the variation in the distribution of the forecasts over time can be used as a measure of uncertainty. Moreover, it is quite easy to implement. This model performs slightly worse than the dynamic factor model within the total evaluation sample, mainly because it is not fully able to catch the large drop in output during the financial crisis. For the post-crisis sample, however, its forecasting performance is even slightly better than the factor model.

Our third approach to extract relevant information from the large data set is *variable selection.* A specific-to-general approach that can handle very large data sets and mixed frequencies is used for this purpose. Although this approach delivers forecasts that are less accurate than those of the information combination approach and the model combination approach, in certain cases, it still offers some improvements against the benchmark.

Additionally, we experimented with pooling the three approaches' forecasts. Forecast pooling of two or three methods delivers very reliable forecasts. Overall, this suggests that it is best to employ several short-term forecast methods on a large data set and to pool the results of the most-promising methods. This is much better than relying on one method that uses only one indicator, and it is particularly beneficial after the financial crisis. Given this finding, we strongly recommend using a large data set and several forecasting approaches when monitoring the Swiss economy.

References

Abberger, K., M. Graff, B. Siliverstovs, and J.-E. Sturm. 2014. "The KOF Economic Barometer, Version 2014: A Composite Leading Indicator for the Swiss Business Cycle." KOF Working Paper No. 353, KOF Swiss Economic Institute.

Angelini, E., G. Camba-Mendez, D. Giannone, L. Reichlin, and G. Rünstler. 2011. "Short-term Forecasts of Euro Area GDP Growth." *Econometrics Journal* 14 (1): C25–C44.

Bańbura, M., D. Giannone, M. Modugno, and L. Reichlin. 2013. "Now-casting and the Real-time Data Flow." In *Handbook of Economic Forecasting*, Vol. 2A, ed. G. Elliot and A. Timmermann, 195–237 (chapter 4). Elsevier.

Bańbura, M., D. Giannone, and L. Reichlin. 2011. "Nowcasting." In *The Oxford Handbook of Economic Forecasting*, ed. M. P.

Clements and D. F. Hendry, 193–224 (chapter 7). Oxford University Press.

Bańbura, M., and M. Modugno. 2014. "Maximum Likelihood Estimation of Factor Models on Datasets with Arbitrary Pattern of Missing Data." *Journal of Applied Econometrics* 29 (1): 133–60.

Bańbura, M., and G. Rünstler. 2011. "A Look into the Factor Model Black Box: Publication Lags and the Role of Hard and Soft Data in Forecasting GDP." *International Journal of Forecasting* 27 (2): 333–46.

Benjamini, Y., and Y. Hochberg. 1995. "Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing." *Journal of the Royal Statistical Society, Series B* 57 (1): 289–300.

Boivin, J., and S. Ng. 2006. "Are More Data Always Better for Factor Analysis?" *Journal of Econometrics* 132 (1): 169–94.

Caggiano, G., G. Kapetanios, and V. Labhard. 2011. "Are More Data Always Better for Factor Analysis? Results for the Euro Area, the Six Largest Euro Area Countries and the UK." *Journal of Forecasting* 30 (8): 736–52.

Castle, J. L., J. A. Doornik, and D. F. Hendry. 2011. "Evaluating Automatic Model Selection." *Journal of Time Series Econometrics* 3 (1): 1–33.

Chudik, A., G. Kapetanios, and M. H. Pesaran. 2016. "Big Data Analytics: A New Perspective." Working Paper.

Doz, C., D. Giannone, and L. Reichlin. 2012. "A Quasi–Maximum Likelihood Approach for Large, Approximate Dynamic Factor Models." *Review of Economics and Statistics* 94 (4): 1014–24.

Drechsel, K., and R. Scheufele. 2012. "The Performance of Short-term Forecasts of the German Economy before and during the 2008/2009 Recession." *International Journal of Forecasting* 28 (2): 428–45.

Evans, M. D. D. 2005. "Where Are We Now? Real-Time Estimates of the Macroeconomy." *International Journal of Central Banking* 1 (2): 127–75.

Foroni, C., and M. Marcellino. 2014. "A Comparison of Mixed Frequency Approaches for Nowcasting Euro Area Macroeconomic Aggregates." *International Journal of Forecasting* 30 (3): 554–68.

Galli, A. 2018. "Which Indicators Matter? Analyzing the Swiss Business Cycle Using a Large-Scale Mixed-Frequency Dynamic Factor Model." *Journal of Business Cycle Research* 14 (2): 179–218.

Giannone, D., L. Reichlin, and D. Small. 2008. "Nowcasting: The Real-time Informational Content of Macroeconomic Data Releases." *Journal of Monetary Economics* 55 (4): 665–76.

Heinisch, K., and R. Scheufele. 2018. "Bottom-up or Direct? Forecasting German GDP in a Data-rich Environment." *Empirical Economics* 54 (2): 705–45.

Herwartz, H. 2011a. "Forecast Accuracy and Uncertainty in Applied Econometrics: A Recommendation of Specific-to-General Predictor Selection." *Empirical Economics* 41 (2): 487–510.

———. 2011b. "Specific-to-General Predictor Selection in Approximate Autoregressions—Monte Carlo Evidence and a Large-Scale Performance Assessment with Real Data." *AStA Advances in Statistical Analysis* 95 (2): 147–68.

Kaufmann, D., and R. Scheufele. 2017. "Business Tendency Surveys and Macroeconomic Fluctuations." *International Journal on Forecasting* 33 (4): 878–93.

Kuzin, V., M. Marcellino, and C. Schumacher. 2011. "MIDAS vs. Mixed-Frequency VAR: Nowcasting GDP in the Euro Area." *International Journal of Forecasting* 27 (2): 529–42.

———. 2013. "Pooling versus Model Selection for Nowcasting GDP with Many Predictors: Empirical Evidence for Six Industrialized Countries." *Journal of Applied Econometrics* 28 (3): 392–411.

Lahiri, K., and G. Monokroussos. 2013. "Nowcasting US GDP: The Role of ISM Business Surveys." *International Journal of Forecasting* 29 (4): 644–58.

Mariano, R. S., and Y. Murasawa. 2003. "A New Coincident Index of Business Cycles Based on Monthly and Quarterly Series." *Journal of Applied Econometrics* 18 (4): 427–43.

Maurer, C., and M. Zeller. 2009. "PMI — aktuelles Konjunkturbarometer der Schweiz." *Die Volkswirtschaft* 3-2009: 51–52.

McCracken, M. W., M. T. Owyang, and T. Sekhposyan. 2015. "Real-time Forecasting with a Large, Mixed Frequency, Bayesian VAR." Working Paper No. 2015-030A, Federal Reserve Bank of St. Louis.

Ng, S. 2013. "Variable Selection in Predictive Regressions." In *Handbook of Economic Forecasting*, Vol. 2, Part B, ed. G. Elliott and A. Timmermann, 753–89 (chapter 14). Elsevier.

Stock, J. H., and M. W. Watson. 2002. "Macreconomic Forecasting Using Diffusion Indexes." *Journal of Business and Economic Statistics* 20 (2): 147–62.

———. 2011. "Dynamic Factor Models." In *The Oxford Handbook of Economic Forecasting*, ed. M. P. Clements and D. F. Hendry, 35–59 (chapter 2). Oxford University Press.

Online Appendix to "Mixed-Frequency Models for Tracking Short-Term Economic Developments in Switzerland"

Alain Galli, Christian Hepenstrick, and Rolf Scheufele
Swiss National Bank

Introduction

This online appendix provides a more detailed exposition of the models under consideration in "Mixed-Frequency Models for Tracking Short-Term Economic Developments in Switzerland." It also provides some additional results that were not reported in the main text.

Information Combination Using a Dynamic Factor Model

As outlined in the main text, we use the EM algorithm as suggested by Doz, Giannone, and Reichlin (2012) and extended by Bańbura and Modugno (2014) to allow for mixed frequencies and arbitrary patterns of missing data. In the following, we describe the model and our particular specification choices in somewhat more detail, explain how we initialize the EM algorithm, and briefly sketch the empirical performance of some alternative model specifications.

Some Details on the Model and Specification

We define our data vector at a monthly frequency as

$$z_t = \begin{bmatrix} x^Q_{q,t} \\ x^M_{m,t} \end{bmatrix}, \tag{1}$$

where the superscripts Q and M denote whether the variable is observed in monthly or quarterly frequency and the subscripts q

and m denote at which frequency the variable is actually computed. For GDP, e.g., $X^{Q}_{i=gdp,q,t}$ denotes the observed quarterly value for GDP in period t, and $X^{Q}_{i=gdp,m,t}$ denotes the (latent) monthly value for GDP in period t. The vector $x^{Q}_{q,t}$ collects the n^{Q} quarterly indicators (observed only in the third month of the quarter) including GDP, whereas the vector $x^{M}_{m,t}$ stacks the n^{M} monthly indicators. The total number of indicators is $n = n^{Q} + n^{M}$.

We stationarize trending quarterly variables using three-month growth rates following Rünstler et al. (2009). Given this choice, we can write the vector of observed indicators z_t as

$$z_t = (G_0 + G_1 L + G_2 L^2) \begin{bmatrix} x^{Q}_{m,t} \\ x^{M}_{m,t} \end{bmatrix}, \tag{2}$$

where $x^{Q}_{m,t}$ is unobserved and

$$G_0 = \begin{bmatrix} \frac{1}{3} I_{n^Q} & \mathbf{O} \\ \mathbf{O} & I_{n^M} \end{bmatrix}, G_1 = \begin{bmatrix} \frac{1}{3} I_{n^Q} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{bmatrix}, G_2 = \begin{bmatrix} \frac{1}{3} I_{n^Q} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{bmatrix}. \tag{3}$$

Defining $\mathbf{G}(L) = (G_0 + G_1 L + G_2 L^2)$, we can write the factor model as $z_t = \mathbf{G}(L)(\Lambda f_t + u_t)$. In state-space form we obtain the following measurement equation:

$$z_t = H_t \underbrace{\begin{bmatrix} f_t \\ f_{t-1} \\ f_{t-2} \end{bmatrix}}_{\substack{\xi_t \\ 3r\times 1}} + \underbrace{\begin{bmatrix} \tilde{u}^{Q}_{t} \\ u^{M}_{t} \end{bmatrix}}_{\epsilon_t}, \tag{4}$$

with $\epsilon_t \sim N(\mathbf{0}_n, R_t)$. $\tilde{u}^{Q}_{t} = G(L) u^{Q}_{t}$ is assumed to be white noise.[1] Note that in z_t, we replace missing values with zeros. Therefore, H_t and R_t are modifications of the matrices

[1]Conceptionally, u^{Q}_{t} would actually follow a moving-average process. However, as outlined in Angelini, Bańbura, and Rünstler (2010), this does not affect the consistency of the estimates. Furthermore, without this assumption, the EM algorithm would not be applicable to factor models with mixed frequencies, as mentioned in Mariano and Murasawa (2010).

$$H = \begin{bmatrix} G_0\Lambda & G_1\Lambda & G_2\Lambda \end{bmatrix} \text{ and } R = \begin{bmatrix} \frac{3}{9}\Sigma_u^Q & \mathbf{O} \\ \mathbf{O} & \Sigma_u^M \end{bmatrix}, \tag{5}$$

with their elements adjusted according to the data situation of period t. That is, if an indicator i is unobserved at time period t, the i-th line of H is replaced with zeros to obtain H_t and the i-th entry of the diagonal of R is replaced with 0 to obtain R_t. Note that this procedure applies to quarterly indicators that are unobserved because t is the first or second month of a quarter as well as to unobserved monthly indicators. More details on how the Kalman filter is able to address missing observations can be found in Durbin and Koopman (2012).

The transition equation representing the VAR of the factors is given by

$$\begin{bmatrix} f_t \\ f_{t-1} \\ f_{t-2} \end{bmatrix} = \begin{bmatrix} \Phi_{r\times r} & \mathbf{O}_{r\times 2r} \\ I_{2r} & \mathbf{O}_{2r\times r} \end{bmatrix} \begin{bmatrix} f_{t-1} \\ f_{t-2} \\ f_{t-3} \end{bmatrix} + e_t, \tag{6}$$

where

$$e_t = \begin{bmatrix} v_t \\ \mathbf{0}_{2r} \end{bmatrix} \sim N\left(\mathbf{0}_{3r}, Q\right), \text{ and } Q = \begin{bmatrix} I_r & \mathbf{O}_{r\times 2r} \\ \mathbf{O}_{2r\times r} & \mathbf{O}_{2r\times 2r} \end{bmatrix}. \tag{7}$$

Obtaining the Starting Values for the EM Algorithm

The model is estimated using the EM algorithm as outlined in Bańbura and Modugno (2014). The starting values for the algorithm are obtained as follows:

(i) Perform a principal component analysis with monthly variables only to obtain the first r principal components f_t^0.

(ii) Regress all variables on the first r principal components to get an initial estimate for Λ:
- For quarterly variables: $x_{i,q,t}^Q = \Lambda_i(f_t^0 + f_{t-1}^0 + f_{t-2}^0)/3 + \epsilon_{i,q,t}^Q$.
- For monthly variables: $x_{i,m,t}^M = \Lambda_i f_t^0 + \epsilon_{i,m,t}^M$.

(iii) Obtain the initial values for $\Sigma_u = \text{diag}(\sigma_1^2, \cdots, \sigma_n^2)$ by using the resulting residual from the regressions above in the following way:
- For quarterly variables: $\sigma_i^2 = \frac{9}{3} V(\epsilon_{i,q,t}^Q)$.
- For monthly variables: $\sigma_i^2 = V(\epsilon_{i,m,t}^M)$.

(iv) Obtain the initial values for Φ by estimating a simple VAR(p) for the first r principal components f_t^0.

Alternative Variable Transformation and Aggregation Scheme for the DFM

Table A1 shows a comparison of the baseline model using three-month growth rates for the non-stationary variables and the alternative specification using month-on-month growth rates and the aggregation rule of Mariano and Murasawa (2003). In all cases, the baseline specification dominates the alternative version.

Table A1. Alternative Data Transformation and Aggregation Rules for DFM

	Early-Quarter Information Set		**Late-Quarter Information Set**	
	$h = 1$	$h = 2$	$h = 1$	$h = 2$
Baseline: Three-Month Growth Rates and 1/3, 1/3, 1/3 Aggregation	1.44	2.02	1.42	1.47
Alternative: Month-on-Month Growth Rates and 1/3, 2/3, 3/3, 2/3, 1/3 Aggregation	1.67	2.03	1.65	1.78

Notes: The table shows root mean squared errors (RMSEs) for $h = 1$ (nowcast) and $h = 2$ (one additional quarter ahead) using two different states of information. "Baseline" corresponds to the DFM model used in the paper and "Alternative" is the aggregation and transformation scheme proposed by Mariano and Murasawa (2003).

Model Combination Using MIDAS Regressions

As explained in the main text, we form the final forecast of the model combination approach by calculating the arithmetic average of all individual models that have a BIC that is smaller than the one of the optimal AR model (GDP regressed on a constant and its own lags, where the number of lags is chosen by BIC). However, we experimented with various alternative combination schemes, which we briefly outline in the following.

Alternative Weighting Schemes

(i) Approximated Bayesian weighting scheme depending on the model's Bayesian (or Schwarz) information criterion. This scheme implies that $w_i^{SIC} = (\exp\left(-0.5 \cdot \Delta_i^{SIC}\right))/(\sum_{i=1}^{n} \exp\left(-0.5 \cdot \Delta_i^{SIC}\right))$ with $\Delta_i^{SIC} = SIC_i - SIC_{\min}$.

(ii) Mallows model averaging (MMA) as proposed by Hansen (2007, 2008). This measure is based on Mallows' criterion for model selection. The goal is to minimize the mean square error (MSE) over a set of feasible forecast combinations. This implies minimizing the function $C = (y - Fw)^{'}(y - Fw) + w^{'}Ks^2$, where K is a vector including the number of coefficients of each model and $s^2 = (\hat{e}(M)^{'}\hat{e}(M))/(T - k(M))$ is an estimate for σ^2 from the model with the smallest estimated error variance. We apply the constraints $0 \leq w \leq 1$ and $\sum_{i=1}^{n} \omega_i = 1$. Note that MMA explicitly takes into account the number of estimated parameters of the model.

(iii) Weights that are inversely proportional to the models' past forecast errors as applied, for example, in Stock and Watson (2004) and Drechsel and Scheufele (2012) to predict output using leading indicators. For concreteness, consider the following example: t denotes the period with the last observation of the target. The weights applied to form the h-period-ahead forecast are calculated by recursively running out-of-sample forecasts for the last $p - 1$ periods and for each indicator i. Based on the corresponding forecast errors $e_{i,t-p+1}, \cdots, e_{i,t}$, the mean square forecast error (MSFE) for each indicator i is calculated, $S_{i,t}^h = \sum_{s=t-p+1}^{t} \left(\hat{e}_{i,s}\right)^2 / p$. The weights that are then used to calculate the final forecast for $t+h$ GDP growth are

$$w_{i,t}^h = \frac{(S_{i,t}^h)^{-1}}{\sum_{j=1}^{n}(S_{j,t}^h)^{-1}}. \tag{8}$$

Note that the mean square forecast error and therefore also the weights are specific to the forecasting horizon h.

(iv) A rank-based weighting scheme. This scheme is also based on the models' past forecast performance; however, the weights are computed using the ranks of the individual models (Aiolfi and Timmermann 2006; Heinisch and Scheufele 2018). It is thus very closely related to the previous combination schemes that use the past MSFEs to calculate the weights. However, instead of relying directly on the MSFEs, the weights are calculated based on the models' ranks: we order the indicators according to the MSFEs, $S_{i,t}^h$, calculated under (iii). The model with the lowest $S_{i,t}^h$ obtains rank 1, $\mathcal{R}_{i,t}^h = f(S_{1,t}^h, \ldots, S_{n,t}^h)$. The weights are then

$$w_{i,t}^h = \frac{(\mathcal{R}_{i,t}^h)^{-1}}{\sum_{j=1}^{N}(\mathcal{R}_{j,t}^h)^{-1}}. \tag{9}$$

One advantage of ranks compared with direct MSFE weights is that they are less sensitive to outliers and, thus, should be more robust. In practice, the weighting scheme based on ranks places very high weight on the group of best models and nearly zero weight on models with less-accurate past performance. Note that the mean square forecast error and therefore also the weights are specific to the forecasting horizon h.

Table A2. Alternative Forecast Combination Approaches

	Total Sample 2005:Q1–2015:Q2		**Post-Crisis Sample 2010:Q1–2015:Q2**	
	$h = 1$	$h = 2$	$h = 1$	$h = 2$
A. Early-Quarter Information				
Benchmark (Mean)	1.6660	2.1831	1.2411	1.1755
SIC	0.999	0.999	1.005*	0.999
MMA	1.140*	1.072	1.283**	1.134
MSE	0.995	1.007	1.037	1.010
RANK	0.982	0.990	1.158*	1.027
B. Late-Quarter Information				
Benchmark (Mean)	1.5604	2.0528	1.1498	1.1701
SIC	0.997	1.000	1.005	1.000
MMA	1.074	1.068	1.153	1.095
MSE	0.979	1.006*	1.028	1.011
RANK	0.969	0.965	1.115	0.995

Notes: The table shows root mean squared errors (RMSEs) for $h = 1$ (nowcast) and $h = 2$ (one additional quarter ahead) using two different states of information. Besides the benchmark based on equal weights, all numbers are defined relative to the benchmark. SIC: weights based on information criterion; MMA: Mallows model averaging; MSE: inverse MSE of previous performance; RANK: inverse of the rank of the previous mean squared performance. ***, **, and * indicate whether a model's predictive ability (using the DM test) is significantly different from the benchmark (at the 1 percent, 5 percent, and 10 percent levels, respectively).

Empirical Performance of the Different Weighting Schemes. Table A2 presents the performance of the different weighting schemes relative to the baseline scheme. No alternative scheme yields a significant improvement relative to the arithmetic mean used in the baseline specification. However, the MMA weights clearly underperform the baseline specification.

Variable Selection Using a Specific-to-General Approach

In the following we describe various elements of the variable selection methodology in somewhat more detail.

Blocking and Realignment

In order to handle mixed frequency, we apply blocking. In particular, we generate for each monthly indicator $x^M_{i,m,t}$ three new quarterly indicators $\tilde{x}^Q_{i,q,t}$, $\tilde{x}^Q_{i,q,t-1}$, and $\tilde{x}^Q_{i,q,t-2}$ for $t = 3, 6, 9, \ldots$. This leaves us with a quarterly data set. However, this data set may still be unbalanced at the current margin due to differing publication lags. We therefore realign the indicator such that the panel becomes balanced.

The LM Statistic and the Critical Value with Which It Is Compared

The LM statistic for indicator k used in steps (iii) and (iv) of the algorithm described in the main text is calculated as $\lambda_k = TR^2_k$ (Godfrey 1988), where R^2_k is the coefficient of determination of the regression of step (iii).

The critical value with which we compare the highest LM statistic in step (v) is the $(1 - \tilde{\alpha})$ quantile of the $\chi^2(1)$ distribution. $\tilde{a}$ depends on the pre-specified significance level α, $\tilde{a} = f(\alpha)$. It is computed according to the false discovery rate control method (as proposed by Benjamini and Hochberg 1995). We use $\alpha = 0.05$.

Note that by setting $\tilde{a} \neq \alpha$, we deviate from the original method proposed by Herwartz (2011a, 2011b). In the case of large data sets, without any adjustment for multiple testing, the danger of overfitting is quite evident. However, by applying a standard Bonferroni adjustment, the probability of selecting an indicator would drop to zero when the size of the data set increases strongly. Therefore, we have to find a compromise between the two issues. The false discovery rate (FDR) achieves exactly that, as it was shown to have much better power properties than standard Bonferroni bounds and still guards against large type I errors.[2] Table A3 shows the performance of the Bonferroni correction and the original method applying no correction relative to our baseline. Bonferroni works similar to our correction, whereas applying no correction performs clearly worse for $h = 1$.

[2]More specifically, we employ the proposed two-step method of Benjamini, Krieger, and Yekutieli (2006).

Table A3. Modifications of the Specific-to-General Approach

	Total Sample 2005:Q1–2015:Q2		Post-Crisis Sample 2010:Q1–2015:Q2	
	$h = 1$	$h = 2$	$h = 1$	$h = 2$
A. Early-Quarter Information				
Benchmark (FDR)	1.5736	2.6475	1.5286	1.8642
Bonferroni	1.004	0.995	0.930	0.876
No Correction	1.182**	0.976	1.007	1.255
B. Late-Quarter Information				
Benchmark (FDR)	1.5739	2.6653	1.5303	1.8846
Bonferroni	1.004	0.992	0.931	0.866
No Correction	1.263**	0.978	1.064	1.253

Notes: The table shows root mean squared errors (RMSEs) for $h = 1$ (nowcast) and $h = 2$ (one additional quarter ahead) using two different states of information. Besides the benchmark procedure, which uses the control of false discovery rate (FDR) of the significance level, all numbers are defined relative to the benchmark. Bonferroni: Bonferroni adjustment; No Correction: no correction for multiple testing. ***, **, and * indicate whether a model's predictive ability (using the DM test) is significantly different from the benchmark (at the 1 percent, 5 percent, and 10 percent levels, respectively).

References

Aiolfi, M., and A. Timmermann. 2006. "Persistence in Forecasting Performance and Conditional Combination Strategies." *Journal of Econometrics* 135 (1–2): 31–53.

Angelini, E., M. Bańbura, and G. Rünstler. 2010. "Estimating and Forecasting the Euro Area Monthly National Accounts from a Dynamic Factor Model." *OECD Journal: Journal of Business Cycle Measurement and Analysis* 2010 (1): 1–22.

Bańbura, M., and M. Modugno. 2014. "Maximum Likelihood Estimation of Factor Models on Datasets with Arbitrary Pattern of Missing Data." *Journal of Applied Econometrics* 29 (1): 133–60.

Benjamini, Y., and Y. Hochberg. 1995. "Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple

Testing." *Journal of the Royal Statistical Society, Series B* 57 (1): 289–300.

Benjamini, Y., A. M. Krieger, and D. Yekutieli. 2006. "Adaptive Linear Step-up Procedures that Control the False Discovery Rate." *Biometrika* 93 (3): 491–507.

Doz, C., D. Giannone, and L. Reichlin. 2012. "A Quasi–Maximum Likelihood Approach for Large, Approximate Dynamic Factor Models." *Review of Economics and Statistics* 94 (4): 1014–24.

Drechsel, K., and R. Scheufele. 2012. "The Performance of Short-term Forecasts of the German Economy before and during the 2008/2009 Recession." *International Journal of Forecasting* 28 (2): 428–45.

Durbin, J., and S. J. Koopman. 2012. *Time Series Analysis by State Space Models.* 2nd Edition. Oxford University Press.

Godfrey, L. G. 1988. *Misspecification Tests in Econometrics.* Cambridge: Cambridge University Press.

Hansen, B. E. 2007. "Least Squares Model Averaging." *Econometrica* 75 (4): 1175–89.

———. 2008. "Least-Squares Forecast Averaging." *Journal of Econometrics* 146 (2): 342–50.

Heinisch, K., and R. Scheufele. 2018. "Bottom-up or Direct? Forecasting German GDP in a Data-rich Environment." *Empirical Economics* 54 (2): 705–45.

Herwartz, H. 2011a. "Forecast Accuracy and Uncertainty in Applied Econometrics: A Recommendation of Specific-to-General Predictor Selection." *Empirical Economics* 41 (2): 487–510.

———. 2011b. "Specific-to-General Predictor Selection in Approximate Autoregressions — Monte Carlo Evidence and a Large-scale Performance Assessment with Real Data." *AStA Advances in Statistical Analysis* 95 (2): 147–68.

Mariano, R., and Y. Murasawa. 2003. "A New Coincident Index of Business Cycles Based on Monthly and Quarterly Series." *Journal of Applied Econometrics* 18 (4): 427–43.

———. 2010. "A Coincident Index, Common Factors, and Monthly Real GDP." *Oxford Bulletin of Economics and Statistics* 72 (1): 27–46.

Rünstler, G., K. Barhoumi, S. Benk, R. Cristadoro, A. Den Reijer, A. Jakaitiene, P. Jelonek, A. Rua, K. Ruth, and C. Van Nieuwenhuyze. 2009. "Short-term Forecasting of GDP Using

Large Datasets: A Pseudo Real-time Forecast Evaluation Exercise." *Journal of Forecasting* 28 (7): 595–611.

Stock, J. H., and M. W. Watson. 2004. "Combination Forecasts of Output Growth in a Seven-Country Data Set." *Journal of Forecasting* 23 (6): 405–30.

Currency Option Trading Strategies as an Alternative Tool for Central Bank Foreign Exchange Interventions*

Helena Glebocki Keefe[a] and Erick W. Rengifo[b]
[a]Fairfield University
[b]Fordham University

Many emerging markets' central banks are concerned with excessive volatility in foreign exchange rates and intervene to smooth volatility. This paper proposes a specific option trading strategy as an alternative central bank tool to aid foreign currency intervention, where dynamic delta hedging of the net portfolio position guides the central bank's intervention in the spot market. We term this trading strategy the "W" spread, and show that the exchange rate can be stabilized and volatility lowered with this market-driven approach to foreign exchange intervention.

JEL Codes: F31, G15.

1. Introduction

Many emerging markets' central banks are concerned with excessive volatility in foreign exchange rates and wish to exert some control over the direction and speed with which the value of their currency

*The authors would like to thank the Global Association for Risk Professionals for their support in the funding of this research, as well as the participants of the First Annual Meeting of the Peruvian Society of Economists and members of the Peruvian Central Bank. The usual disclaimers apply. Author contact: Keefe: Department of Economics, Fairfield University, Fairfield, CT 06824 (USA), (203) 254-4000, e-mail: hkeefe@fairfield.edu. Rengifo: Department of Economics and the Center for International Policy Studies (CIPS), Fordham University, 441 East Fordham Road, Dealy Hall, Office E513, Bronx, NY 10458. Phone: 718-817-4061, Fax: 718-817 3518.

changes. Historically, intervention methods have relied on the purchase and sale of foreign currency directly in the spot market.[1] This paper proposes a specific option trading strategy as an alternative central bank tool to aid foreign currency intervention, where dynamic delta hedging of the net portfolio position guides the central bank's intervention in the spot market.[2] The main objective of the central bank in adopting this type of an intervention strategy is to limit exchange rate volatility with an intervention position that is driven by market forces. It is important to note that no intervention strategy can overcome the effects of structural changes that cause exchange rate movements, but this strategy can dampen the effects of sudden exchange rate shocks and lower volatility. Because the strategy responds to market conditions, rather than subjective interventions determined by policymakers, it may be more effective in responding to shocks than discretionary spot market interventions.

We use the Colombian central bank's experience with volatility options as a benchmark[3] and analyze an option trading strategy that we term the "W" spread, where the central bank holds a portfolio of two long calls, two long puts, one short call, and one short put.[4] The proposed intervention happens on two fronts. First, on a daily basis, the spot market purchase/sale of USD will be determined by the responsiveness of the option price to a change in the daily exchange rate—or the option's delta. Second, at maturity, the central bank as well as the market participants can use the proceeds from the option execution to buy/sell USD on the spot market that once again complements the central bank's goal of stabilizing exchange

[1] More recently, central banks in Brazil, India, Mexico, and Turkey have been intervening through the derivatives market. See Domanski, Kohlscheen, and Moreno (2016) and Nedeljkovic and Saborowski (2017).

[2] We tested a variety of traditional strategies first that did not reach the intended goal of lowering volatility through both daily interventions and at exercise. Results are available upon request.

[3] Colombia is one of the only economies known to have used currency options as a means for curbing exchange rate volatility. This strategy has been found to be successful in reaching the stated goals of smoothing the volatility (Keefe and Rengifo 2015).

[4] In all cases, the options are in U.S. dollars (USD). For example, in a long call position, the central bank has the right to buy USD from the issuer of the option. In a short call position, the central bank has the obligation to sell USD to the owner of the option.

rate movements. Our results show that since the spot market interventions are now driven by the delta of the option, the central bank lowers volatility with a clear, market-driven position.

The remaining sections of the paper are structured as follows. Section 2 provides a review of the literature. Section 3 describes the W-spread option trading strategy and argues why this strategy is an improvement on others already used in the market. Section 4 presents the analytical approach and methodology. Section 5 reports the results by testing the W-spread strategy with a simulated series of the Colombian peso–U.S. dollar exchange rate (COPUSD). Here we price options contracts at various strike prices and analyze the outcome of dynamically delta hedging the net portfolio position and its effect on exchange rate movements. Section 6 concludes.

2. Literature Review

There is limited literature on the use of currency options by central banks for the purpose of exchange rate intervention. In the past, the proposition for emerging market central banks to use currency options has been more of a theoretical exercise. This may be partly due to the relatively shallow and underdeveloped derivatives markets in these economies. Despite the recent growth in demand for foreign exchange derivatives in emerging economies, they represent only a fraction of the global derivatives market. Emerging markets make up only 4.4 percent of the daily over-the-counter (OTC) trading of foreign exchange derivatives according to data collected by the Bank for International Settlements (BIS).[5] Yet, there is demand for these financial products. Turnover in foreign exchange derivatives for emerging market economies has increased by over 300 percent from 2001 to 2013.

Furthermore, options made up only 6 percent of the total foreign exchange derivatives market traded in emerging economies as of 2010 (Mihaljek and Packer 2010). Adoption of options-based intervention tools by central banks may aid further development of these markets. Local traders as well as export/import businesses would have a

[5]This excludes the top four derivatives trading centers of Hong Kong, Singapore, Korea, and Brazil, which make up over 90 percent of the total emerging market derivatives trading (Mihaljek and Packer 2010).

new hedging instrument readily available to them. Caballero (2003) contends that emerging markets need instruments for hedging and insurance purposes against capital flow reversals, specifically, and the exchange rate volatility that they may cause. In comparing Australia and Chile, Caballero illustrates how emerging markets require insurance to assist in the response to crises and shocks that would match the effectiveness of policy responses in advanced economies.

There have been a number of arguments for the adoption of a derivatives-based intervention strategy. Wiseman (1999) argues that governments should commit themselves to frequent and regular auctions of short-dated physically delivered currency options as a mechanism to stabilize exchange rates. Since almost all central bank authorities would like to reduce exchange rate volatility, without pushing it all the way to zero, official auctions would encourage private banks to buy options and exercise them when profitable. Dynamic delta hedging on the part of the trader can substitute for actively pursuing the same position in the market.

Zapatero and Reverter (2003) consider the intervention strategies of central banks when directly intervening in the spot market using foreign exchange reserves compared with intervention with the use of options. With the counterparty investment bank hedging its position, the options intervention method performs better than traditional spot market intervention using foreign exchange reserves. The currency stabilization occurs through the hedging activities of the investment bank in the bond market to offset its currency options position with the central bank.

Keefe and Rengifo (2015) analyze the success of volatility options used by the Colombian central bank to mitigate deviations of the exchange rate from the twenty-day moving average. In 85 percent to 90 percent of options executed, the value of the COPUSD reverted towards the trend, thereby successfully minimizing the volatility. After abandoning the strategy in 2009, the Colombian central bank has once again instituted the use of volatility options as of October 2015.

A fundamental assumption in our strategy is the use of dynamic delta hedging to guide the open-market intervention position of central banks. According to Breuer (1999), if market makers hold net long positions, their dynamic delta-hedging behavior can lower volatility. When the owners of an option contract sell USD in the spot market to hedge their positions when the domestic currency is depreciating against the dollar, and purchase USD when the domestic currency is appreciating against the dollar, this will help stabilize exchange rates. Furthermore, the transparency with which the central bank auctions option contracts to market participants may introduce stability and additional hedging instruments into the market (Archer 2005). Garber (1994) and Malz (1995) also study the effects of hedging on currency stabilization. By influencing market liquidity and expectations, the use of currency options by central banks can be effective in stabilizing the exchange rate and controlling volatility.

Testing the effectiveness of foreign exchange interventions has been complicated, since the size, frequency, and duration of intervention may vary drastically within and between countries. The most thorough analysis of intervention effectiveness to date has been conducted by Fratzscher et al. (2015) by studying foreign exchange intervention in thirty-three countries. They find that foreign exchange intervention is widely used by a number of countries, and that it is an effective policy to smooth and stabilize exchange rates.

Daude, Levy Yeyati, and Nagengast (2014) review the effectiveness of traditional foreign exchange intervention in emerging market economies, specifically with the reassessment of this tool in the wake of the global financial crisis. The authors find that the most effective interventions are those that are used as a countercyclical macroeconomic tool, smoothing out short-run volatility and currency swings. Interventions can slow appreciation, and are most effective when the currency is already overvalued. Their effectiveness decreases under conditions of greater capital account openness (Adler and Tovar 2011).

Leon and Williams (2012) concur that foreign exchange intervention via either purchase or sale of foreign currency is effective if the goal is to keep the exchange rate within a targeted range. The interventions are an appropriate policy tool in emerging economies looking to control imported inflation while maintaining competitiveness. Egbert (2007) finds that interventions in emerging European economies were successful in curbing appreciation pressure, while Guinigundo (2013) shows that by using spot market interventions as the main tool for intervention, the central bank of the Philippines was able to curb exchange rate volatility without adhering to a specific level of the exchange rate. The results in this paper support that finding. Akinci et al. (2006) also found that purchase-based interventions were successful in curbing appreciation.

Our research contributes to the literature on both the potential use of currency options by central banks and the potential effectiveness of such tools in curbing exchange rate volatility. By proposing a novel trading strategy that allows the central bank to operate in both the spot and derivatives market, we explore a new approach to the question of how central banks in emerging market economies can effectively intervene in currency markets to reach their objective of smoothing exchange rate volatility.

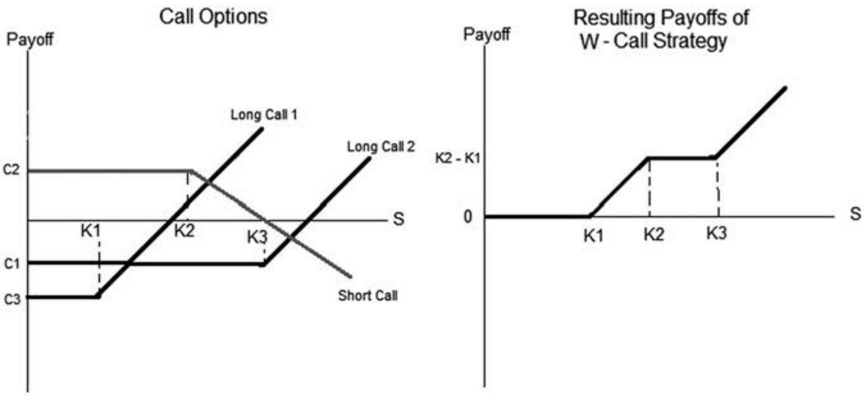
3. W-Spread Strategy

The W-spread strategy has two key components. First, in the options market, the central bank portfolio position consists of two long calls, one short call, two long puts, and one short put, where the underlying asset is the U.S. dollar (USD). With this portfolio combination of calls and puts, the exercise of the options at maturity contributes to the intervention objectives of the central bank. Second, the dynamic delta hedging of this portfolio on a daily basis determines the central bank's daily spot market purchase/sale of USD in a way that once again complements its intervention objectives.[6] The use of options creates a stronger signaling channel between the policymakers and market participants because those following the market will have a clear understanding of the actions of the central bank. The option delta and the delta hedging inform both market participants and the central bank of intervention positions and act as an announcement via the market.

Although the central bank will incur costs in the form of premiums paid for buying the long options and payoffs paid when the short

[6]The combination of long and short positions as well as call and put options is the crucial element of this strategy. By holding both sides of the market, the central bank limits the opportunity for market manipulation, and the intervention is driven by the responsiveness of the options' market price to changes in the exchange rate. With this strategy, the intervention position of the central bank in the spot market is now driven by the delta of the option and therefore is determined by market forces.

Figure 1. W-Call Spread



Notes: The W-call spread presents a position with limited risks but unlimited gains in case of depreciation beyond K_3. It consists of one short call with strike price K_2, one long call with strike price K_1, and one long call with strike price K_3. The middle strike price (K_2) for the short position is determined as $\frac{K_1+K_3}{2}$.

option positions are exercised, central banks will also receive positive payoffs when the long options are exercised plus the premiums received from the sales of options. As will be presented in section 5, the potential costs of the strategy are offset by the potential gains, making the strategy a near-zero net expected returns/losses.

3.1 Details of W-Spread Strategy

To understand the W-spread strategy, consider first the call side and the put side separately.[7] Figure 1 depicts the W-call spread, which consists of two long call positions with a strike price of K_1 and K_3, and one short position with a strike price of K_2. The middle strike price for the short position is determined as $\frac{K_1+K_3}{2}$. For the W-call spread strategy, as the spot exchange rate value depreciates beyond K_3, the central bank gains $S - K_2$ at maturity, as seen in table 1. The gains continue to increase as the spot exchange rate, S, increases (local currency depreciates). On the other hand, if S

[7]The underlying asset for all options is the U.S. dollar, and all option contracts are European and therefore cannot be exercised until maturity.

Table 1. W-Call Spread Payoffs

	Calls			
	Long Call (K_1)	**Short Call (K_2)**	**Long Call (K_3)**	**Total**
$S \leq K_1$	0	0	0	0
$K_1 \leq S < K_2$	$S - K_1$	0	0	$S - K_1$
$K_2 \leq S < K_3$	$S - K_1$	$-(S - K_2)$	0	$K_2 - K_1$
$S \geq K_3$	$S - K_1$	$-(S - K_2)$	$S - K_3$	$S - K_2$

Note: This table presents the payoffs that would be paid by the issuer of the short call and received by the owner of the long calls.

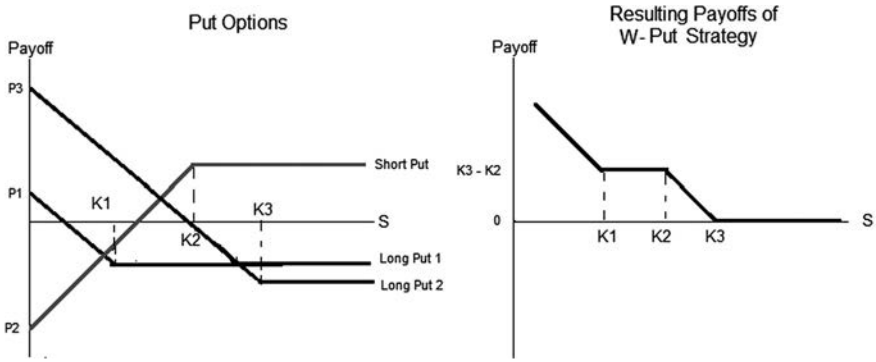
appreciates beyond K_1, all call options will expire without being exercised and the losses will be limited to the premiums paid on the long call options.

The net cost to the central bank will be the premium paid on the long call options plus the payoff on the short call option if it is exercised. As can be seen, the losses are limited to the premium paid on the long options, but the gains are unlimited if the currency depreciates beyond K_3. It would be counterintuitive for the central bank to attempt to move the market into a deep depreciation, as we assume that the goals of the central bank to maintain stability prevail over any objective to maximize gains.

The W-put spread presented in figure 2 consists of two long put positions with strike prices at K_1 and K_3, and one short put with a strike price of K_2. The middle strike price for the short position is determined as $\frac{K_1+K_3}{2}$. Once again, the strategy offers unlimited gains and limited losses in payoffs. As the currency value appreciates beyond K_1, the central bank obtains a payoff of $K_2 - S$, as seen in table 2, which increases as the spot exchange rate, S, continues decreasing (local currency appreciates). On the other hand, if the exchange rate depreciates beyond K_3, all put options expire without being exercised and the only losses the central bank faces are those of the long put option premiums.

As can be seen in both W-call spread and W-put spread strategies, the risks are limited and the gains unlimited if the exchange rate moves beyond the strike price K_3 for the W-call spread and K_1

Figure 2. W-Put Spread



Notes: The W-put spread presents a position with limited risks and limited gains. It consists of one short put with the strike price K_2, one long put with strike price K_1, and one long put with strike price K_3. The middle strike price (K_2) for the short position is determined as $\frac{K_1+K_3}{2}$.

Table 2. W-Put Spread Payoffs

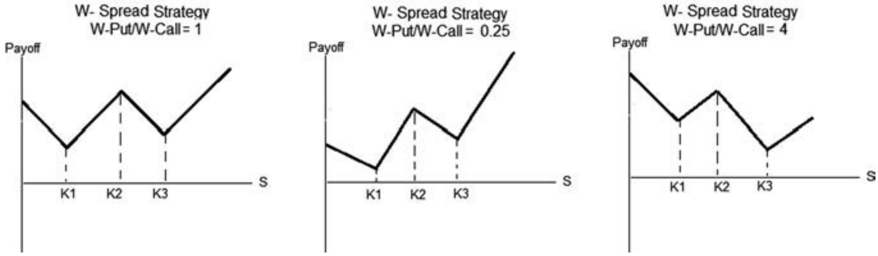
	Puts			
	Long Put (K_1)	**Short Put (K_2)**	**Long put (K_3)**	**Total**
$S < K_1$	$K_1 - S$	$-(K_2 - S)$	$K_3 - S$	$K_2 - S$
$K_1 \leq S < K_2$	0	$-(K_2 - S)$	$K_3 - S$	$K_3 - K_2$
$K_2 \leq S < K_3$	0	0	$K_3 - S$	$K_3 - S$
$S \geq K_3$	0	0	0	0

Note: This table presents the payoffs that would be paid by the issuer of the short put and received by the owner of a long put.

for the W-put spread. Combining both spreads creates the W-spread strategy, depicted in figure 3. In a neutral W-spread strategy, there is an equal distribution of funds into the W-call spread and W-put spread strategy, depicted by the graph on the left in figure 3.[8] The

[8]We refer to the even split in W-puts/W-calls in the W-spread strategy as "neutral" because the weight of the delta hedging (purchase or sale of USD) based on appreciation or depreciation will be equal between the W-put spreads and W-call spreads.

Figure 3. W-Spread Strategy

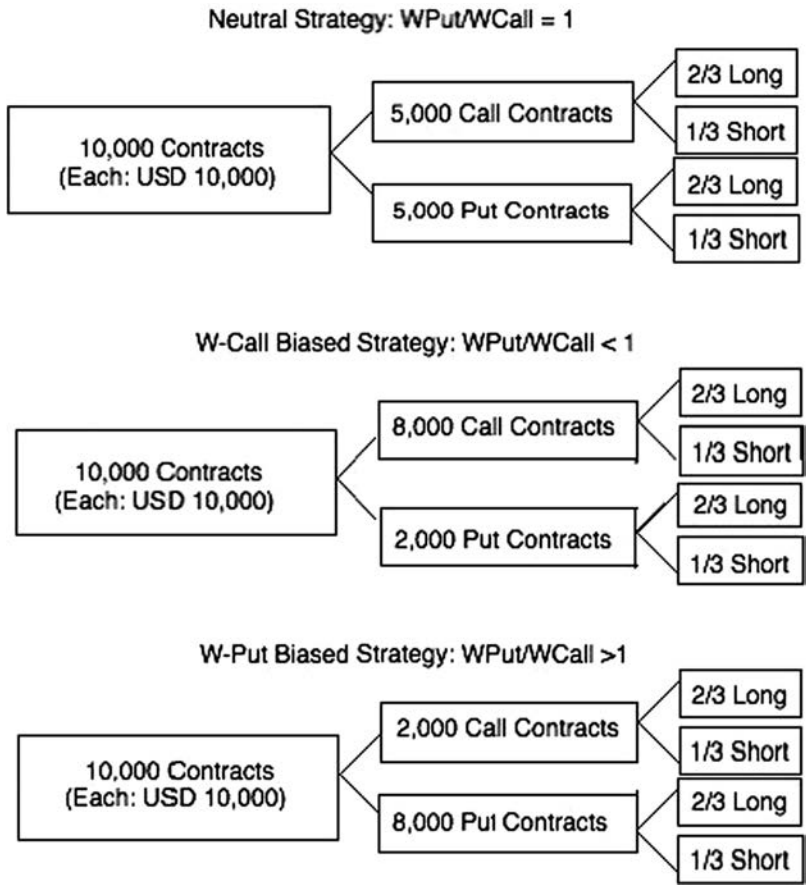


Notes: The W-spreads with calls and puts presents a position with limited risks and unlimited gains. It consists of combining the W-call spread with the W-put spread. In a neutral position, the W-put/W-call spread ratio is 1, depicted in the left graph. In a call-biased W-strategy, the W-put/W-call spread ratio is 0.25, depicted in the middle graph. In a put-biased W-strategy, the W-put/W-call spread ratio is 4, depicted in the right graph.

neutral strategy is used as the characteristic example to explain how the strategy functions. In reality, if the central bank is observing persistent movement of the exchange rate or strong expectations of appreciation or depreciation of the currency, it can and should enact a biased strategy.

In a biased strategy, the portfolio is weighted heavier with either W-calls or W-puts, as is illustrated in figure 3 and figure 4. In an appreciationary scenario, the central bank adjusts its strategy to reflect the actual or expected appreciation of the domestic currency. More traders would be seeking put options, which for the long position provide protection against further appreciation and on the short side allow them to bet the appreciation will be curbed (working in favor of the central bank's goals). In a put-biased strategy, the central bank holds a relatively larger concentration of W-puts to W-calls in the portfolio. If 10,000 contracts are traded as part of the intervention strategy, 80 percent of the contracts would be allocated towards W-put spreads, and the remaining 20 percent towards W-calls. The W-put/W-call ratio would be 4. The net dynamic delta-hedging activity of the central bank leading up to maturity will force the central bank to buy USD on the spot market, thereby countering the appreciation pressure more strongly than in a neutral position

Figure 4. Distribution of W-Spread



Notes: In a neutral position, the W-put/W-call spread ratio is 1. In a call-biased W-strategy, the W-put/W-call spread ratio is 0.25, and would be enacted under conditions of strong depreciation. In a put-biased W-strategy, the W-put/W-call spread ratio is 4, and would be enacted under conditions of strong appreciation.

(the explanation for how the hedging works will be provided in detail below).

Conversely, under conditions of depreciation of the local currency, a portfolio weighted heavier with W-calls than W-puts would be appropriate. In this scenario, more market participants are seeking out call options in general. For the long position, the call options would protect against losses associated with further depreciation of the currency, whereas market participants holding short positions are betting that the depreciation will be curbed before maturity (again, an action that would complement the goals of the central bank in this scenario). The net dynamic delta-hedging activity of the central bank leading up to maturity will force the central bank to sell USD on the spot market, thereby countering the depreciation pressure more strongly than in a neutral position. The biased strategies can be employed in conditions when there are expectations of strong or persistent depreciation (ratio smaller than 1) or appreciation (ratio larger than 1), so that the central bank is essentially "doubling up" on its effort to combat the deviations of the exchange rate.

It is important to note that the weights associated with the central bank's portfolio may be adjusted continuously to reflect market conditions. There is nothing precluding the central bank from waiting until maturity to issue a new set of options. Nor must the date be fixed to thirty days, which is a relatively short time span that allows adjustment as is deemed necessary. If the central bank begins in a neutral strategy, but more calls are transacted than puts, by default it is now holding a W-call-biased strategy. Therefore, the adjustment can be either overt, based on the weights assigned by the central bank, or dictated by demand from market participants. In either case, the weights, and thereby the intervention, adjusts to reflect market realities.

Table 3 details the payoffs associated with the W-strategy. In the top panel of table 3, the payoffs at maturity for the neutral W-spread strategy are presented, showing the position of the central bank when all contracts have expired or have been exercised. The lower two panels of table 3 show the payoffs for a call-biased and put-biased W-spread strategy. As can be seen, the W-spread strategy yields the potential for unlimited gains with limited risk. When the exchange rate at maturity, S, moves beyond strike prices K_1 or K_3, this results in payoffs greater than zero which increase as S is farther from the strike prices. When the exchange rate at maturity is between strike prices K_1 or K_3, the payoffs for the central bank are still positive even though limited in size. The same holds true for the biased strategies, as can be seen in the lower panels of table 3.

Table 3. W-Spread Strategy Payoffs

	Calls				**Puts**				**Net**
	Long Call (K_1)	**Short Call (K_2)**	**Long Call (K_3)**	**Total**	**Long Put (K_1)**	**Short Put (K_2)**	**Long Put (K_3)**	**Total**	
W-Put/W-Call Spread = 1									
$S < K_1$	0	0	0	0	$K_1 - S$	$-(K_2 - S)$	$K_3 - S$	$K_2 - S$	$K_2 - S > 0$
$K_1 \leq S < K_2$	$S - K_1$	0	0	$S - K_1$	0	$-(K_2 - S)$	$K_3 - S$	$K_3 - K_2$	$S - 2K_1 + K_2$
$K_2 \leq S < K_3$	$S - K_1$	$-(S - K_2)$	0	$K_2 - K_1$	0	0	$K_3 - S$	$K_3 - S$	$3K_2 - 2K_1 - S$
$S \geq K_3$	$S - K_1$	$-(S - K_2)$	$S - K_3$	$S - K_2$	0	0	0	0	$S - K_2 > 0$
W-Put/W-Call Spread = 0.25									
$S < K_1$	0	0	0	0	$K_1 - S$	$-(K_2 - S)$	$K_3 - S$	$K_2 - S$	$K_2 - S > 0$
$K_1 \leq S < K_2$	$4(S - K_1)$	0	0	$4(S - K_1)$	0	$-(K_2 - S)$	$K_3 - S$	$K_3 - K_2$	$4S - 5K_1 + K_2$
$K_2 \leq S < K_3$	$4(S - K_1)$	$-4(S - K_2)$	0	$4(K_2 - K_1)$	0	0	$K_3 - S$	$K_3 - S$	$6K_2 - 5K_1 - S$
$S \geq K_3$	$4(S - K_1)$	$-4(S - K_2)$	$-4(S - K_3)$	$4(S - K_2)$	0	0	0	0	$4(S - K_2) > 0$
W-Put/W-Call Spread = 4									
$S < K_1$	0	0	0	0	$4(K_1 - S)$	$-4(K_2 - S)$	$4(K_3 - S)$	$4(K_2 - S)$	$4(K_2 - S) > 0$
$K_1 \leq S < K_2$	$S - K_1$	0	0	$S - K_1$	0	$-4(K_2 - S)$	$4(K_3 - S)$	$4(K_3 - K_2)$	$S - 5K_1 + 4K_2$
$K_2 \leq S < K_3$	$S - K_1$	$-(S - K_2)$	0	$K_2 - K_1$	0	0	$4(K_3 - S)$	$4(K_3 - S)$	$9K_2 - 5K_1 - 4S$
$S \geq K_3$	$S - K_1$	$-(S - K_2)$	$(S - K_3)$	$S - K_2$	0	0	0	0	$S - K_2 > 0$

Notes: This table presents the payoffs that would be paid by the issuer of the short put and call and received by the owner of the long put and call. This table presents W-put/W-call spread ratios of 1, 0.25, and 4.

The costs the central bank faces include the premium it must pay to hold the long option positions and the payoffs it must pay for the short positions when the contracts are exercised. Table 3 takes into account the net payoffs, and therefore already accounts for the cost of paying the short position payoffs. Theoretically, the accumulated delta-hedging transactions until maturity, measured by the cumulative financial costs incurred, equal the options' premiums.[9] Moreover, the net payoffs obtained in any of the W-spread strategies cover the costs associated with premiums paid by the central banks. This is particularly true for deep in-the-money or out-of-the-money final exchange rates. On average, by pairing the W-spread strategy with dynamic delta hedging, the central bank is able to cover its hedging costs with the net payoffs, creating a position where in fact the central bank does not face compounding gains or losses, presenting another positive advantage for central banks to incorporate dynamic delta hedging as part of the options-based intervention strategy. We show this in several simulations presented in section 5.

3.2 Details of Dynamic Delta Hedging

The W-spread strategy's dynamic delta hedging informs the central bank of the correct size of USD to purchase or sell on the spot market in order to cover its option positions. With dynamic delta hedging, the central bank can reduce volatility by providing (reducing) liquidity and by clearly signaling its intentions to all market participants. Since the delta of the option captures the responsiveness of the option value to changes in the spot exchange rates and because these changes can be estimated on a daily basis, hedging based on the delta of the option provides the central bank with a market-driven strategy to guide its spot market interventions.

The delta of the option is the derivative of the option price with respect to the spot exchange rate and can be presented as follows (DeRosa 2011, Chen 1998):

$$\delta_{call} = e^{-r^*\tau}\Phi(x + \sigma\sqrt{2}) \tag{1}$$

$$\delta_{put} = e^{-r^*\tau}\left(\Phi(x + \sigma\sqrt{2}) - 1\right), \tag{2}$$

[9]For example, see Hull (2012, chapter 7).

where

$$x = \frac{ln\frac{S_t}{K} + \left(r - r^* + \frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{2}}$$

and $0 \leq \delta_{call} \leq 1$ for call deltas and $-1 \leq \delta_{put} \leq 0$ for put deltas.

The delta of the option is influenced by the daily spot exchange rate (S), the foreign interest rate (r^*), the domestic interest rate (r), the strike price (K), and volatility (σ). Therefore, as the central bank responds to changes in the deltas of the options in its portfolio, it is responding in essence to changes in each of these variables.

To understand how the hedging of the W-spread strategy contributes to the intervention goals of central banks, we must first consider what occurs during the hedge. Dynamically delta hedging a long call on USD when the local currency depreciates implies that the owner of the option sells USD in the domestic spot market.[10] By doing so, the supply of USD in the spot market rises, thereby introducing appreciation pressures that counter the depreciation of the local currency. Similarly, by dynamically delta hedging a long-put position as the local currency depreciates, the owner of the long put sells USD in the domestic spot market to offset his position at maturity of the option contract. The offsetting spot market positions contribute to appreciation pressure that counters the depreciation of the local currency (COP, for example). These scenarios are summarized in table 4.

In the W-spread strategy, the central bank hedges the net portfolio position (recall that the W-spread strategy is made of two long calls, one short call, two long puts, and one short put). Therefore, whether it is buying or selling USD depends on the aggregated deltas of each of the six options in the portfolio. As we demonstrate in the following section, the W-spread strategy is designed specifically so that the buying/selling of the foreign currency through the hedge contributes to countering the deviations of the exchange rate.

[10]The long call gives the owner the option to buy USD at the strike price at a given future time. For these owners, depreciation benefits them since their payoff is given by max(S–K,0). Thus, at any time during the life of the option, they should (short) sell whenever $S_t > K$ and buy whenever $S_t < K$. Of course, this implies first that the owner is comfortable performing periodic delta hedges and that the financial costs associated with it are adequately considered.

Table 4. Impact of Dynamic Delta Hedging on Exchange Rate Movements

	Dynamic Delta-Hedging Position			
	Calls		**Puts**	
	Long	**Short**	**Long**	**Short**
Depreciation	Short-Sell USD *Counters*	Buy USD *Exacerbates*	Short-Sell USD *Counters*	Buy USD *Exacerbates*
Appreciation	Buy USD *Counters*	Short-Sell USD *Exacerbates*	Buy USD *Counters*	Short-Sell USD *Exacerbates*

Note: This table presents the overall daily dynamic delta-hedging outcomes under conditions of depreciation or appreciation for short and long positions for calls and puts.

3.3 Dynamics of the W-Spread Strategy

As presented previously in figure 4, the mix of W-call and W-put spreads in the central bank's portfolio may be altered to reflect the expectations of the persistent exchange rate movements. First, if the central bank wants to hold a position that does not signal expectations of depreciation or appreciation, they can evenly distribute their portfolio between the W-call spread and W-put spread (W-put/W-call spread ratio equal to 1). By doing so, their daily interventions via the delta-hedging position are equally large for an appreciation or depreciation of their currency.

On the other hand, if there are expectations of persistent appreciation or depreciation (not driven by fundamentals), accompanied by high volatility in the market, the central bank can choose to hold a biased W-spread portfolio to signal a stronger intervention in response to the persistent and not fundamentals-driven appreciation or depreciation, as discussed above. For example, with persistent depreciation, the central bank can hold a call-biased W-spread. Under this strategy and on a daily basis, the central bank's delta hedging in the spot market implies a net sale of USD that is greater than under the neutral W-spread strategy (W-put/W-call spread ratio equal to 1). Through the sales of USD on the spot market, the central bank counteracts the persistent depreciation and contributes to decreasing volatility by providing greater liquidity into the market. With persistent appreciation, the central bank can hold a put-biased W-spread. Under this strategy and on a daily basis, the central bank's delta-hedging interventions in the spot market imply a net purchase of USD which is greater than under the neutral W-spread strategy. Through the purchase of USD on the spot market, the central bank counteracts the persistent appreciation by absorbing excess liquidity of USD into the market.

For every option the central bank holds or issues, there is an offsetting position by a market participant that has purchased or sold the option. The risk associated with the offsetting positions of market participants is derived from the delta hedging of short positions, which may exacerbate the movements in the exchange rate. Delta hedging of the long position complements the goals of the central bank.[11] Since options act as a risk-management tool for many corporations and traders, market participants can choose to hedge all, part, or none of their net portfolio positions. In many cases, the option itself acts as a hedge against other positions the market participants are holding. Since hedging can be costly, not all market participants hedge their entire portfolio position. Additionally, in derivatives markets not all the participants are willing, interested, or capable of delta hedging their positions on a daily basis. The desire to hedge depends on the nature of the business under consideration (trading, international trade—exporters and importers, among others) and their knowledge of the derivatives markets. In the appendix, three potential scenarios are presented where the offsetting market positions are hedged 100 percent, 50 percent, and 10 percent, while the central bank hedges 100 percent of both long and short positions. If the cumulative offsetting market positions are hedged by less than 100 percent, then the central bank's dynamic delta-hedging position provides an intervention strategy that is conducive to its goals of stabilizing exchange rate movements.

We focus on the W-spread in this paper after testing various other traditional strategies. We develop the W-spread because the central element which drives the day-to-day intervention is the delta hedging conducted by the central bank. This element, along with the option value, acts to influence the exchange rate both through

[11] Examples are shown in the appendix.

the volume transacted and through the signaling channel, where the anticipation of central bank intervention in reaction to exchange rate movements influences the position of traders. The hedging of other strategies traditionally considered for central bank usage, such as short calls or short puts, along with other trading strategies, such as the short straddle or short strangle, exacerbate the exchange rate movements the central bank is attempting to curb.[12]

Dynamic delta hedging is a critical element of any option trading strategy adopted by policymakers to mitigate losses and avoid the excessive buildup or drawdown of foreign exchange reserves. By the nature of the hedge, the equivalent volume of foreign or domestic currency that will be transacted at maturity will already by accumulated through the delta hedge. Therefore, the intervention does not create a need to alter the level of foreign exchange reserves in the medium term. Through the delta hedging, the reserves will return to the original pre-intervention level at exercise.

The W-spread strategy also has a number of important byproducts associated with it. By using options to guide its interventions, the central bank is creating or deepening the options market while strengthening the institutional framework that previously either did not exist or was very shallow, as is the case in many emerging market economies.[13] By operating in the options market, the central bank is assisting in creating a deeper risk trading platform for the private sector. Additionally, the greater information flow between market participants and policymakers that occurs when the central bank participates in options contracts will strengthen the responsiveness of the central bank to market conditions and thereby allow policymakers to act more effectively in ensuring that optimal market conditions are in place. Central banks in emerging markets can also get valuable information from traders' behavior and expectations that can be implied from these markets. In this way, intervention

[12]More detailed explanation and intervention impact analysis using these strategies is available upon request.

[13]Note that the creation and support of these markets has sizable economic value. The beneficiaries of derivatives markets include FX traders, exporters and importers, and any other economic agent wanting to hedge foreign exchange risk. Therefore, by contributing to the creation of these risk markets, central banks are advancing financial market development, which is important for economic growth.

via the options market provides a two-way information platform that can convey useful information for all participants.

4. Methodology

In testing the W-spread strategy, the goal is to understand whether at maturity and with daily dynamic delta hedging the central bank is able to mitigate exchange rate volatility. We focus on the following conditions: persistent depreciation, depreciation with a shock, persistent appreciation, appreciation with a shock, and volatility in the exchange rate with no specific trend.

First, we simulate the W-spread strategy with no impact on exchange rates to illustrate how the dynamic delta-hedging element reacts to exchange rate movements. Then, we incorporate the impact of the daily interventions on the exchange rate to analyze how the intervention lowers volatility. We use a random generation of exchange rates within set bounds such as deviations between (–0.10%, +0.10%); (–0.25%, + 0.25%); (–0.50%, +0.50%); (–0.50%, +0.10%); (–0.50%, +0.25%); (–0.10%, +0.25%); (–0.10%, +0.50%); (–0.25%, +0.50%) of the COPUSD with starting values between 1995 and 2010 and an average daily change of +/– 0.12 percent. We also include a "shock" in the second series of simulations with intervention impact analysis. The shock size was a deviation in the exchange rate by between +/– 1.25 percent and +/– 5.0 percent. This shock reflects a drastic increase/decrease in the COPUSD value to mirror a time of distress in the markets.

Using a simulated series of the COPUSD, we calculate the option deltas, from which we establish daily USD purchases/sales. The volume of purchases/sales through the delta hedge determines the intervention position of the central bank on the spot market.

To start, we use the following strike prices in the results presented below:

$$K_{1,0} = 0.9975 * S_0$$

$$K_{3,0} = 1.0025 * S_0$$

$$K_{2,0} = \frac{K_{1,0} + K_{3,0}}{2},$$

where S_0 represents the spot market exchange rate one day before issuance of the W-spread strategy and the strike prices are very close to at-the-money position. After the volatility and strike prices are determined, we estimate the call and put deltas using the Garman-Kohlhagen model as per equations (1) and (2) including Colombia's risk-free interest rate, the U.S. risk-free interest rate, and the simulated exchange rate series. The time to maturity for all contracts is thirty days.

For our analysis, the portfolio consists of 10,000 contracts, with each contract worth USD 10,000. The total value of these contracts is then USD 100 million. It is simple to alter the contract size and total number of contracts transacted, and we have tested the impact of such changes on the W-spread strategy.[14] In accordance with the descriptions presented in section 3, we simulate the use of a neutral W-spread strategy (W-put/W-call spread equal to 1), a call-biased W-spread (W-put/W-call spread less than 1), and a put-biased W-spread (W-put/W-call spread greater than 1). With a neutral strategy, there is an even distribution between W-puts and W-calls, with 5,000 contracts in each (W-put/W-call spread equal to 1). In the call-biased W-spread, there are 8,000 contracts allocated to the W-call spread and 2,000 contracts allocated to the W-put spread (W-put/W-call spread equal to 0.25). In the put-biased W-spread, there are 2,000 contracts allocated to the W-call spread and 8,000 contracts allocated to the W-put spread (W-put/W-call spread equal to 4).

4.1 Daily Transactions

In the dynamic delta hedge, the central bank purchases/sells USD daily based on the delta of the option. Therefore, we calculate total USD purchased or sold on a daily basis, the daily interest cost, and daily cumulative value transacted.

The USD transacted on the spot market on day t for option i is calculated as the difference between the option delta on day t and $t-1$ multiplied by the option contract size. For one contract, the USD transacted ($SpotDelta_{t,i}$) based on the dynamic delta hedge will be

[14] Results are available upon request.

$$SpotDelta_{t,i} = (\delta_{t,i} - \delta_{t-1,i}) * X, \tag{3}$$

where X represents USD per contract or the contract size, which is USD 10,000 in this analysis, and $\delta_{t,i}$ represents the delta of option i on day t. Recall that in the W-spread strategy, we have two long calls and one short call (W-call spread) as well as two long puts and one short put (W-put spread), thus $i = 1 \ldots 6$. For example, $\delta_{15,sp}$ represents the delta of the short put on day 15.

The total net USD transacted via the dynamic delta hedge is calculated as

$$DailySpotDelta_t = \sum_{i=1}^{6} (SpotDelta_{t,i} * Q_i). \tag{4}$$

Again, $SpotDelta_{t,i}$ represents the delta hedge for one contract and Q_i represents the number of contracts issued per type of options i with $\sum_{i=1}^{6} Q_i = 10{,}000$. Each type of option has its contract size that can vary. For our analysis, we assume equal contract size across options unless otherwise stated. Moving forward, we will refer to the total W-spread strategy option value of USD 100 million as Y, where $Y = Q * X$ (the number of contracts multiplied by the contract size).

The cumulative value of the daily transactions ($DailyCV_t$) at $t = 1$ equals the total USD transacted on the spot market. For $t > 1$, the cumulative daily transactions are calculated as

$$DailyCV_t = DailyCV_{t-1} + IntC_{t-1} + DailySpotDelta_t. \tag{5}$$

The daily cumulative USD transacted includes the potential cost for the central bank to conduct the hedge in the form of the interest costs ($IntC_t$). The interest costs paid to obtain (or borrow) USD[15] at time t are determined as

$$IntC_t = \left(e^{\frac{r}{365}} - 1\right) DailyCV_{t-1}, \tag{6}$$

where r represents the domestic interest rate, which for our simulations is the Colombian interbank lending rate.

[15] In this paper we consider this cost even though central banks normally do not have this cost, since they can borrow from their international reserves. We are taking a more conservative stance here.

4.2 End-of-Period Transactions

To present the total accumulated USD transacted at maturity (T), we calculate the end-of-period USD transacted ($EOPVT_T$) as

$$EOPVT_T = DailyCV_T + NetPayoffs_T, \tag{7}$$

where $DailyCV_T$ is the cumulative USD transacted at maturity, i.e., $T = 30$. As seen in the previous equation, $EOPVT_T$ depends on the accumulated value of the USD from the dynamic delta hedge and the net payoffs.

Net payoffs can be divided into long payoffs, which are revenues for the central bank, and short payoffs, which are costs for the central bank. The net payoffs at maturity are presented in table 5, showing the resulting payoffs for the W-spread strategy at all possible outcomes for the exchange rate at maturity, S_{30}.

Table 6 presents a summary of calculations of costs and gains associated with the W-spread strategy and dynamic delta hedging at maturity. It includes the accumulated USD transacted through delta hedging, the interest costs, the net payoffs for both the long and short positions, and the long and short premiums. The premiums of each contract will be paid by the central bank in the long positions and received by the central bank in the short positions. The net gains of the W-spread strategy are represented as

$$\begin{aligned} NetGains_T = {} & (LongPayoff_T + ShortPremium_T) - (IntC_T \\ & + ShortPayoff_T + LongPremium_T). \end{aligned} \tag{8}$$

We refer to $NetGains_T$ as the profit/cost of the W-spread strategy, since it is possible that the central bank can profit from the strategy. Specifically, the gains of the W-spread strategy in the form of long payoffs and short premiums could outweigh the costs, as they do under conditions of persistent depreciation or appreciation that we present in section 5.

The analysis of the daily position of the central bank along with the position at maturity with respect to the amount of USD transacted, the payoffs, and the costs of the strategy will provide insight into the ability of the central bank to employ the W-spread strategy to smooth drastic exchange rate movements and reach its intervention goals. It is important to consider both the daily and at-maturity

Table 5. Payoffs with W-Spread Segmentation

End of Period ($T = 30$)		Definition of F	
$S < K_1$	$F_2(K_1 + K_3 - K_2 - S)$	W-Put/W-Call Spread = 1	$F_1 = \frac{0.5*Y}{3}$; $F_2 = \frac{0.5*Y}{3}$
$K_1 < S \leq K_2$	$F_1(S - K_1) + F_2(K_3 - K_2)$	W-Put/W-Call Spread = 4	$F_1 = \frac{0.2*Y}{3}$; $F_2 = \frac{0.8*Y}{3}$
$K_2 < S \leq K_3$	$F_1(K_2 - K_1) + F_2(K_3 - S)$	W-Put/W-Call Spread = 0.25	$F_1 = \frac{0.8*Y}{3}$; $F_2 = \frac{0.2*Y}{3}$
$S \geq K_3$	$F_1(S + K_2 - K_1 - K_3)$		

Notes: This table presents the payoff structure based on the W-spread strategy segmentation. Y represents the total USD transacted, which is the contract size (USD 10,000) multiplied by the total number of contracts (10,000).

Table 6. Summary of Cost Calculations at Maturity

	End of Period (T = 30)
	W-Spread Strategy
End-of-Period USD Transacted	$DailyCV_T + NetPayoffs_T$
Interest Cost	$IntC_T = (e^{\frac{r}{365}} - 1) DailyCV_{T-1}$
Long Payoff	$\sum_{j=1}^{4}[max(S_T - K_1, 0) * Y_j + max(K_1 - S_T, 0) * Y_j]$ $+ \sum_{j=1}^{4}[max(S_T - K_3, 0) * Y_j + max(K_3 - S_T, 0) * Y_j]$
Short Payoff	$-\sum_{j=1}^{2}[(max(S_T - K_2, 0) + max(K_2 - S_T, 0)] * Y_j)$
Long Premium	$-\sum_{j=1}^{4}(LongOptionPrice_i) * Y_j$
Short Premium	$\sum_{j=1}^{2}(ShortOptionPrice_i) * Y_j$
Profit/Cost of Option Strategy	$(LongPayoff + ShortPremium)$ $-IntC_T + ShortPayoff + LongPremium)$
Share of Total	$Profit/Y$ or $Cost/Y$

Notes: Y represents the contract size, which is USD 10,000 multiplied by the total number of contracts, or 10,000. The payoff structure will depend on the segmentation of the W-spread strategy and the distribution of W-puts to W-call spreads, as seen in table 5.

positions with respect to the four possible scenarios: $S_{30} < K_1$; $K_1 \leq S_{30} < K_2$; $K_2 \leq S_{30} < K_3$; and $S_{30} \geq K_3$. The simulations in the following section provide clear insight into all four possible outcomes.

4.3 Intervention Impact Analysis

To determine how the W-strategy may affect exchange rate volatility, we simulate the COPUSD movements under the following conditions: persistent depreciation, depreciation with a shock, persistent appreciation, appreciation with a shock, and volatility with no set trend. For the simulations we use a linear price impact function,[16]

[16]We thank the referee for suggesting to include this analysis in the paper.

where the change in the exchange rate is a function of the volume transacted. It is important to note that data on volume (amount of dollars bought per intervention) of central banks' intervention is not available, and thus we rely on a statistical method to derive possible linear impact functions.

To estimate the linear approximation of the price impact function, the moving average over thirty days of the COPUSD from 2010 to 2013 is used, yielding 1,370 observations. The changes in the thirty-day moving average are then calculated and classified into appreciation (–1) or depreciation (1) of the COPUSD. The confidence intervals are then computed, per side, using a 95 percent confidence level. In this way, we determine the upper and lower limits for the exchange rate movements when the Colombia peso appreciates or depreciates. We use the lower and upper limits as the limits of the price impact functions, thereby assuming that the interventions have a lower (upper) impact on the exchange rate equal to the lower (upper) limit of the confidence intervals. For this simulation we assume that the lowest purchased (sold) amount of USD corresponds to USD 1 million up to USD 100 million. This yields a linear price change based on the volume transacted, from USD 1 million to USD 100 million, giving an approximation of how the COPUSD reacts to a given quantity (volume) purchase/sale of USD. Finally, we use a simple OLS estimation to determine the coefficients which will allow us to estimate the price impact that will be used to determine the approximate impact of the quantity bought or sold as mandated by the delta-hedging strategy. The impact of volume on the currency exchange is then modeled as

$$P = \alpha + \beta V + \mu, \tag{9}$$

where P represents the exchange rate change, α represents the coefficient for the price impact, β represents the coefficient corresponding to the impact of volume on the exchange rate, and V represents volume transacted. μ represents the iid error term. The OLS regression is run separately for appreciation and depreciation values, since the impact of intervention may differ under each.

With this information we start the simulation to determine the impact of acting according to the delta hedge based on the W-strategy presented in the paper. We do this by simulating random values of the COPUSD to reflect the conditions mentioned before. To compare our results, we keep the original random exchange rates, i.e., values of the exchange rate without intervention (FX). We calculate the delta based on the changes of FX from day 0 to day 1. The delta will determine the volume of USD purchased/sold (V) as explained above. Once we have calculated the volume transacted, we determine the impact on this such that

$$FX_{new} = (\hat{\alpha} + \hat{\beta}V) + FX, \tag{10}$$

where FX_{new} represents the new COPUSD value based on the price impact, V is the volume transacted in the spot market based on delta hedging, and FX represents the COPUSD generated without intervention impact. We continue to calculate the deltas now based on FX_{new} for the next day and continue estimating the value of COPUSD with the intervention impact based on the delta hedging. This simple linear approximation allows us to test how the delta hedging based on the W-strategy can affect the exchange rate. Once we have these numbers (FX without intervention and FX_{new} with volume impact on the exchange rates), we calculate the standard deviations and compare the effect of the intervention on volatility. We use the same approach to calculate the effect of a neutral W-strategy compared with a biased W-strategy to determine whether the biased strategy described in section 3.1 is more effective in lowering volatility.

5. Results

In presenting the results of the W-spread strategy analysis, we begin with a general perspective on the outcomes at maturity considering the key components of the strategy—the option exercise and the daily hedging. Then, we present the results of the simulations under scenarios of persistent depreciation and persistent appreciation with no impact, and finally the simulations accounting for the impact of the daily dynamic delta hedging.

The possible outcomes at maturity are presented in table 7 in terms of option exercise, share of W-spread strategy exercised, and the net amount of USD transacted based on where the spot exchange rate at maturity lands in relation to each strike price. The four scenarios depicted align with the scenarios discussed in table 5 in section 4.

Consider the first scenario, where S_{30} is less than strike price K_1 (or an appreciation of the local currency). In this scenario, the central bank sells USD at a higher price than S_{30} through the long put positions that are exercised at K_1 and K_3. Under a neutral W-spread strategy, the central bank sells USD 16.6 million, meaning that it has an equivalent of USD 16.6 million in local currency ($16.6 \times S_{30}$) that can be used to buy USD to counter appreciation pressure. Also, by buying USD from the owners of the put positions at K_2, the central bank helps to decrease the selling pressure in the spot market. This is true because the owners of the short puts of the W-put spread at K_2 are selling USD to the central bank instead of to the market, which in turn relieves some of the selling pressure and, again, helps to counteract the appreciation pressure on the local currency. Moreover, if the owner of the W-put spread at K_2 wants to make a profit on their purchase,[17] they need to buy USD at S_{30} from the market in such a way that achieves a positive payoff ($K_2 - S_{30} > 0$), contributing with a buying pressure that counters appreciation. Finally, by exercising the central bank's two long put positions, the offsetting short put positions will have no incentive to sell USD in the spot market, since they bought USD from the central bank at a price higher than S_{30} based on the option contract. It would be unwise for the traders holding the offsetting short put positions to turn around and sell the USD purchased from the central bank through the option contract because this would lead to a scenario where they are buying high and selling low. Therefore, the likelihood that their activity would increase selling pressure of USD in the local market is low. Note that this impact increases with higher appreciation expectations where the W-put/W-call spread ratio moves from 1 to 4.

[17]Note, the long put position at K_2 is exercised when $K_2 > S_{30}$.

Table 7. W-Spread Strategy Results at Maturity

	W-Put/W-Call = 1	**W-Put/W-Call = 4**	**W-Put/W-Call = 0.25**
$S_{30} < K_1$			
Sell USD at K_1 (Long Put)	$-0.5\frac{Y}{3}$	$-0.8\frac{Y}{3}$	$-0.2\frac{Y}{3}$
Sell USD at K_3 (Long Put)	$-0.5\frac{Y}{3}$	$-0.8\frac{Y}{3}$	$-0.2\frac{Y}{3}$
Buy USD at K_2 (Short Put)	$0.5\frac{Y}{3}$	$0.8\frac{Y}{3}$	$0.2\frac{Y}{3}$
Net Transacted	$-0.5\frac{Y}{3}$	$-0.8\frac{Y}{3}$	$-0.2\frac{Y}{3}$
Net Transacted in USD	−16.6 million	−26.6 million	−6.6 million
$K_1 \leq S_{30} < K_2$			
Buy USD at K_1 (Long Call)	$0.5\frac{Y}{3}$	$0.2\frac{Y}{3}$	$0.8\frac{Y}{3}$
Sell USD at K_3 (Long Put)	$-0.5\frac{Y}{3}$	$-0.8\frac{Y}{3}$	$-0.2\frac{Y}{3}$
Buy USD at K_2 (Short Put)	$0.5\frac{Y}{3}$	$0.8\frac{Y}{3}$	$0.2\frac{Y}{3}$
Net Transacted	$0.5\frac{Y}{3}$	$0.2\frac{Y}{3}$	$0.8\frac{Y}{3}$
Net Transacted in USD	16.6 million	6.6. million	26.6 million

(*continued*)

Table 7. (Continued)

	W-Put/W-Call = 1	**W-Put/W-Call = 4**	**W-Put/W-Call = 0.25**
	$K_2 \leq S_{30} < K_3$		
Buy USD at K_1 (Long Call)	$0.5\frac{Y}{3}$	$0.2\frac{Y}{3}$	$0.8\frac{Y}{3}$
Sell USD at K_3 (Long Put)	$-0.5\frac{Y}{3}$	$-0.8\frac{Y}{3}$	$-0.2\frac{Y}{3}$
Sell USD at K_2 (Short Call)	$-0.5\frac{Y}{3}$	$-0.2\frac{Y}{3}$	$-0.8\frac{Y}{3}$
Net Transacted	$-0.5\frac{Y}{3}$	$-0.8\frac{Y}{3}$	$-0.2\frac{Y}{3}$
Net Transacted in USD	−16.6 million	−26.6 million	−6.6 million
	$S_{30} \geq K_3$		
Buy USD at K_1 (Long Call)	$0.5\frac{Y}{3}$	$0.2\frac{Y}{3}$	$0.8\frac{Y}{3}$
Buy USD at K_3 (Long Call)	$0.5\frac{Y}{3}$	$0.2\frac{Y}{3}$	$0.8\frac{Y}{3}$
Sell USD at K_2 (Short Call)	$-0.5\frac{Y}{3}$	$-0.2\frac{Y}{3}$	$-0.8\frac{Y}{3}$
Net Transacted	$0.5\frac{Y}{3}$	$0.2\frac{Y}{3}$	$0.8\frac{Y}{3}$
Net Transacted in USD	16.6 million	6.6 million	26.6 million

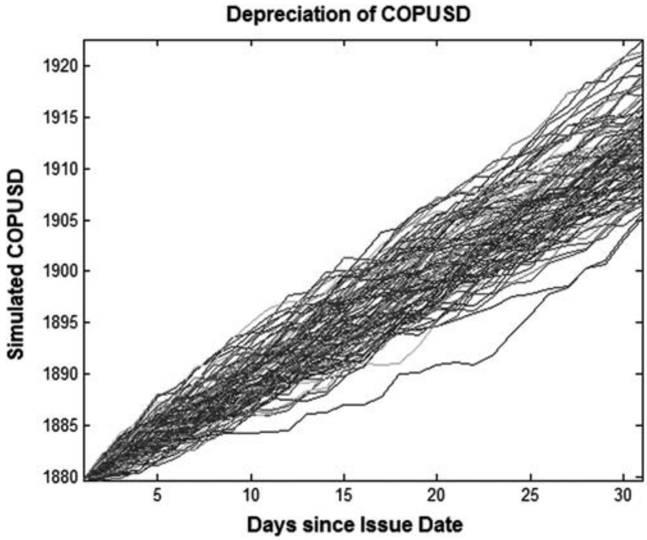
Notes: This table presents the action at maturity with the W-spread strategy segmentation based on the relationship between the spot exchange rate at day 30 (S_{30}) and the three strike prices (K_1, K_2, K_3). Y is the contract size (USD 10,000) multiplied by the total number of contracts (10,000), therefore Y equals USD 100 million. Positive values represent purchases and negative values represent sells.

If we analyze the last case ($S_{30} \geq K_3$), where there is depreciation of the local currency, the reverse action is be observed. Specifically, under the neutral W-spread strategy, the central bank buys USD 16.6 million that can be sold to counter the depreciation pressure. Also, by selling USD to the owner of the call (long call) at K_2, the central bank can help decrease the buying pressure in the spot market, again helping to counteract the depreciation of the local currency. This is true because the long call positions at K_2 are buying USD from the central bank rather than from the market, which in turn relieves some of the buying pressure. Moreover, traders with the long call position that want to cash their positive payoffs need to buy USD in the spot market ($S_{30} - K_2 > 0$). Finally, by exercising the central bank's two long call positions, the offsetting short call positions will have no incentive to buy USD in the spot market, since they sold USD to the central bank at a price lower than S_{30} based on the option contract. It would be unwise for the traders holding the offsetting short call positions to turn around and buy USD on the spot market, because this would lead to a scenario where they are buying high and selling low. Therefore, the likelihood that their activity would increase buying pressure of USD in the local market is low. Note that this impact increases with higher depreciation expectations where the W-put/W-call spread ratio moves from 1 to 0.25. For the intermediate cases ($K_1 \leq S_{30} < K_2$ and $K_2 \leq S_{30} < K_3$) more discretion is necessary since there is no clear appreciation or depreciation pressure.

5.1 Simulation with Persistent Depreciation

We begin with the simulated exchange rates series that presents persistent depreciation in the COPUSD. In these simulations, the intervention impact function has not been included and the goal is to test whether the W-strategy aligns with the goals of the central bank. Figure 5 illustrates the simulation. Figures 6 and 7 present the calculated dynamic delta-hedging position and daily cumulative USD transacted during a period of depreciation. In figure 6 we present a neutral W-spread strategy where the ratio of W-puts to W-call spreads equals 1. In figure 7 we present a call-biased W-strategy where the ratio of W-puts to W-call spreads is less than 1. The daily USD transacted represents the actual amount of USD

Figure 5. Series of Simulated Exchange Rates for Periods with Persistent Depreciation

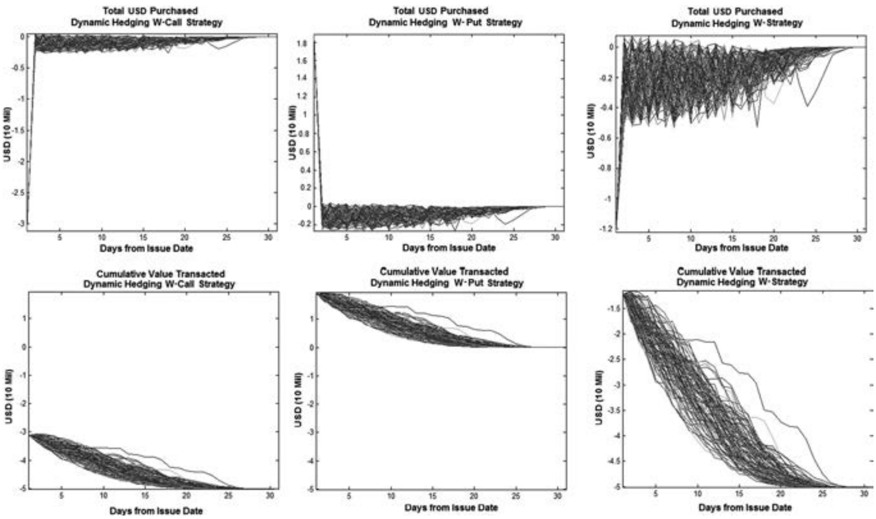


Notes: Exchange rates are simulated using a uniform pseudo-random distribution to represent periods of persistent and significant depreciation. The starting value of simulation is based on the ten-day average COPUSD exchange rates ending on October 20, 2012. Maximum depreciation in this simulation equals 1,922 Colombian pesos per U.S. dollar, which is a 2.23 percent depreciation over thirty days.

the central bank is buying or selling in the spot market based on the net portfolio position and is determined by the deltas of each option contract in the portfolio. Positive values indicate net purchases, whereas negative values indicate net sales. The daily cumulative value transacted includes the interest costs and shares purchased/sold of the foreign currency in the spot market denominated in local currency (COP).

There are three scenarios depicted in each figure. The first is a W-call spread strategy, where the central bank is holding (long) and issuing (short) call options. The second is a W-put spread strategy, where the central bank is holding (long) and issuing (short) put options. The last is a W-spread strategy that combines the W-call and W-put spreads. According to the W-call spread position delta,

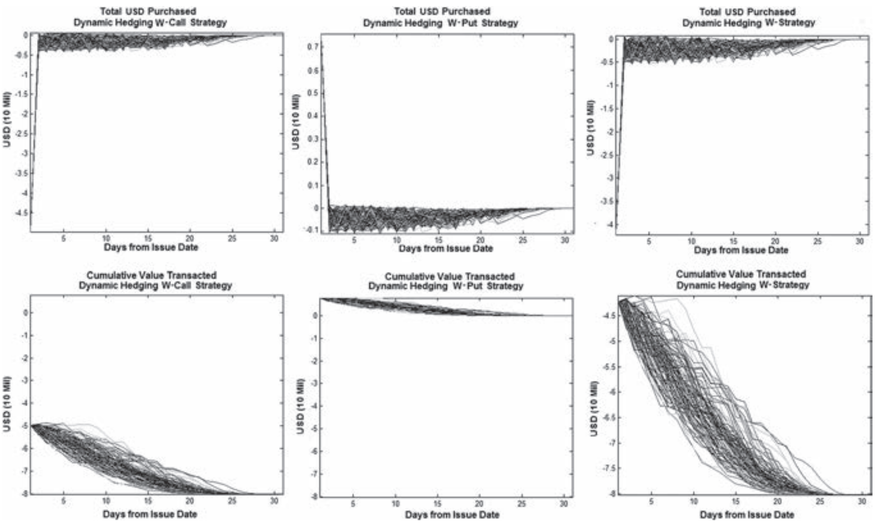
Figure 6. Depreciation Dynamic Delta-Hedging Outcomes (W-put/W-call spread: 1)



Notes: The dynamic delta-hedging position is calculated for 100 series for a thirty-day contract period. By construction, the simulated exchange rates are steadily depreciating over the thirty-day period. The W-spread strategy presented here is a neutral one since the W-put/W-call spread ratio is 1. As can be seen, holding a position in both a W-call spread and W-put spread strategy is the least disruptive to the spot market.

the first-day initial spot market position is substantial, requiring the central bank to sell approximately USD 30 million of foreign currency (USD) in the spot market. Throughout the period to maturity, the net call portfolio position will require the central bank to continue selling USD in the spot market to dynamically delta hedge its options portfolio. By doing so, it in turn introduces a counteracting pressure to the persistent depreciation of the simulated series because, all else equal, the consistent sale of USD by the central bank should contribute to driving down the value of the foreign currency relative to the local currency, leading to an appreciation of the Colombian peso. Under a W-put spread position, the central bank initially conducts a large purchase of USD in the spot market and subsequently sells off its initial spot market position throughout the

Figure 7. Depreciation Dynamic Delta-Hedging Outcomes (W-put/W-call spread: 0.25)



Notes: The dynamic delta-hedging position is calculated for 100 series for a thirty-day contract period. By construction, the simulated exchange rates are steadily depreciating over the thirty-day period. The W-spread strategy presented here is a call-biased one since the W-put/W-call spread ratio is 0.25. As can be seen, holding a position in both a call and put strategy is the least disruptive to the spot market.

period to maturity. In the first day, the central bank buys approximately USD 18 million. Note that if the W-put spread is considered independently, the initial purchase may exert an undesired impact on the exchange rate. Specifically, it would contribute to the depreciation pressure observed in figure 5 by increasing the value of the foreign currency to local currency, leading to further depreciation of the Colombian peso. However, the net position of the W-spread strategy (third column of figures 6 and 7) show that the spot market interventions have the potential to counteract the depreciation pressure. Specifically, the net spot market transactions suggest a large sale of USD followed by small sales that in reality should help to relieve some of the depreciation pressure as the relative supply of USD to COP on the spot market increases, all else equal.

The cumulative value transacted is known and limited, as can be seen in the bottom three graphs of figures 6 and 7. The cumulative value transacted takes into account the accumulation of sales/purchases of USD to hedge the net portfolio position throughout the time to maturity as well as the interest costs associated with the transactions. In the call-biased W-spread strategy, presented in figure 7, the central bank sells more USD on the initial day than in the neutral strategy presented in figure 6, but does not notably change the spot market position in the remaining days leading to maturity. By changing the ratio of W-call spreads and W-puts in the W-spread strategy, the central bank can alter its initial position in the spot market in such a way that makes the initial intervention larger, which may counter the persistent movement of the exchange rate more significantly upfront. The ratio can also signal to the market that the central bank is trying to more strongly counteract the depreciation.

The total value transacted represents the accumulated daily dynamic delta-hedging transactions and interest costs throughout the contract period. Presented in table 8 is the outstanding position of the central bank from its hedging operations and its options contracts, which includes the hedging costs, payoffs, and premiums as described in table 6. Table 8 illustrates the average across all 100 series and depicts the value of transactions for series when the portfolio position is neutral (W-put/W-call spread ratio is 1) as well as for a call-biased portfolio (W-put/W-call spread ratio less than 1) during a period of depreciation.

As can be seen in table 8, the total cumulative interest costs are low considering that the total outstanding USD in option contracts is USD 100 million. The net value transacted throughout the option contract is determined by the W-put/W-call spread ratio.[18] Since only the W-call spreads are exercised when the spot market price depreciates above the strike price K_3, the outstanding volume of USD the central bank is obligated to transact is covered by the net value collected from their long positions. The W-puts expire out of the money and will not be exercised, as the currency depreciates

[18]As a percentage of the total option value (USD 100 million), the net value transacted is only 0.52 percent and 1.14 percent for the neutral and call-biased strategies, respectively.

Table 8. End-of-Period Dynamic Delta Costs, Payoffs, and Premiums

	Average Across Series (USD)			
	W-Put/W-Call = 1	**St. Dev.**	**W-Put/W-Call = 0.25**	**St. Dev.**
End-of-Period USD Transacted	−50,108,000	3,613	−80,188,000	3,884
Interest Cost	−112,200	3,613	−195,360	3,884
Long Payoff	2,474,600	5,271	3,908,700	8,524
Short Payoff	−1,237,300	2,636	−1,954,400	4,262
Long Premium	−659,160	1,404	−812,580	1,772
Short Premium	314,630	670	391,340	853
Profit/Cost of Option Strategy	780,550	4,938	1,337,700	6,423
Share of Total	0.78%	0.005%	1.34%	0.006%

Notes: "End-of-Period USD Transacted" represents the cumulative value of daily dynamic delta hedging and interest costs. Each contract size is USD 10,000 and there are 10,000 contracts issued. The table depicts the costs for series when the portfolio position is neutral (W-put/W-call spread ratio of 1) as well as for a call-biased portfolio (W-put/W-call spread ratio of 0.25) during a period of depreciation. The calculations reflect those described in the summary table 6. The negative values reflect a cost or outlay of funds for the central bank, whereas the positive values reflect funds acquired by the central bank. "Profit/Cost of Option Strategy" is the sum of the long payoff and short premium minus the sum of the net value transacted, interest cost, short payoff, and long premium.

above K_3.[19] The initial purchase position on the first day for the W-puts is offset by the subsequent smaller sales throughout the contract period. Therefore, the central bank is only transacting on the spot market the amount needed to cover its option obligations. By doing so, it limits excessive reserve accumulation and purchases/sells USD according to the relationship between the exchange rate and option price, or the delta of the option.

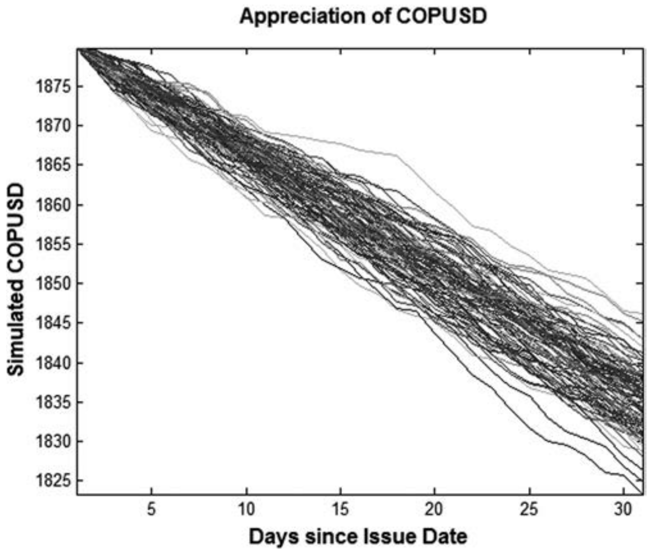
5.2 Simulation with Persistent Appreciation

The next analysis tests the use of the W-spread strategy under scenarios with persistent appreciation. Figure 8 illustrates the simulation. Figures 9 and 10 present the calculated dynamic delta-hedging position and the daily cumulative value transacted during a period of persistent appreciation. Once again, three scenarios are presented in each figure. If we consider only the W-call spread strategy, the initial spot market position requires the central bank to sell approximately USD 30 million in day 1. This move contributes to local currency appreciation and, as such, can be potentially destabilizing to the market. However, after this initial selling and throughout the period to maturity, the net portfolio position requires the central bank to buy USD in the spot market to dynamically delta hedge its position. The daily purchases of USD may in turn introduce a counteracting pressure to the persistent appreciation by driving up the value of USD relative to the domestic currency.

Considering the W-put spread alone, the central bank initially conducts a large purchase of USD in the spot market (approximately USD 18 million) and continues purchasing USD throughout the period to maturity. By continually purchasing USD on the spot market, the hedging activity of the central bank alters the relative supply of USD to COP in the spot market in a way that may introduce depreciation pressure to counter the persistent appreciation,

[19] It is important to note that the exercise of each of the puts or calls will be determined by whether the spot exchange rate at maturity is greater than or less than the corresponding strike price. In the scenario presented here, the spot exchange rate has depreciated above K_3, which is 1,884.

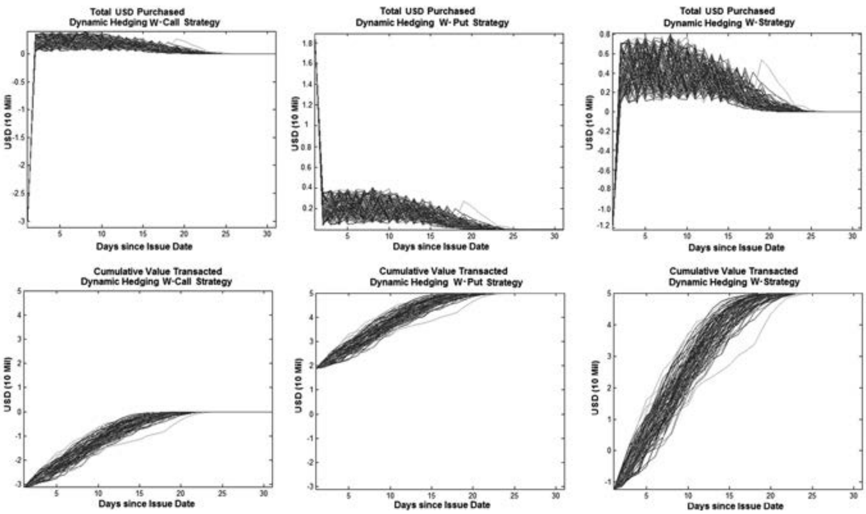
Figure 8. Series of Simulated Exchange Rates for Periods with Persistent Appreciation



Notes: Exchange rates are simulated using a uniform pseudo-random distribution to represent periods of appreciation. The starting value of the simulation is based on the ten-day average COPUSD exchange rates ending on October 20, 2012. Maximum appreciation in this simulation is 1,824, which is a 2.97 percent appreciation over thirty days.

all else equal. Note that in the neutral W-spread strategy (third column in figure 9), the central bank initially sells USD, but then continually purchases USD over the period to maturity. However, since the initial position is a sale of USD 12 million, it may be sizable enough to contribute to the appreciation, and therefore counter the goals of the central bank. In this case, by altering the W-put/W-call spread ratio more heavily towards the W-put spread, as seen in figure 10, the central bank can avoid this situation and now purchase USD 17 million in the spot market on the initial day of the contract and continue to purchase USD throughout the period to maturity (third column in figure 10). Altering the ratio not only signals to the market that the central bank is acting to curb the appreciation, but also that the spot market hedging position of the

Figure 9. Appreciation Dynamic Delta-Hedging Outcomes (W-put/W-call spread: 1)

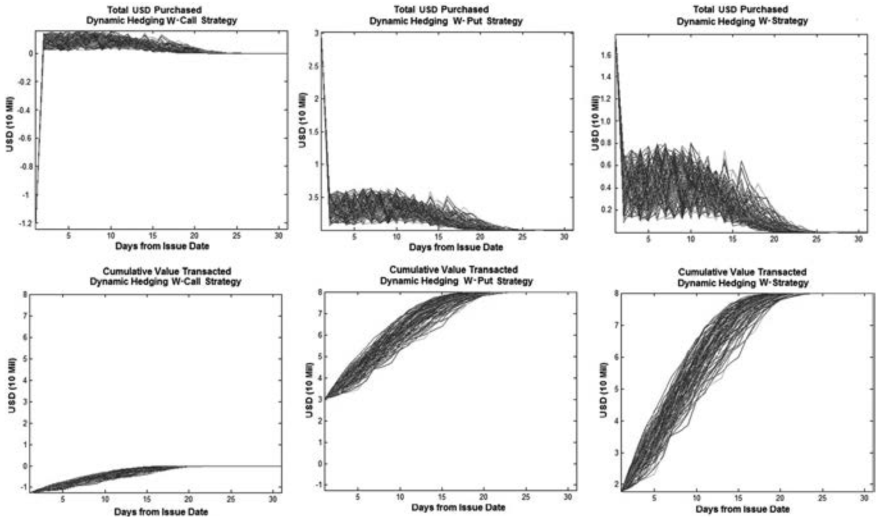


Notes: The dynamic delta-hedging position is calculated for 100 series for a thirty-day contract. The exchange rate is steadily appreciating over the period to maturity. The W-put/W-call spread ratio is 1. As can be seen, holding a position in both a W-call spread and W-put spread strategy is the least disruptive to the spot market.

central bank may drive up the relative price of USD to COP and act to counter the appreciation.

Table 9 depicts the value of transactions for series when the portfolio position is neutral (W-put/W-call spread ratio equal to 1) as well as for a put-biased portfolio (W-put/W-call spread ratio equal to 4) during a period of appreciation. The calculations reflect those described in the summary table 6. Once again, the total cumulative interest costs are low considering that the total outstanding USD in option contracts is USD 100 million (0.09 percent and 0.17 percent for W-put/W-call spread ratios of 1 and 4, respectively). The net value transacted throughout the option contract is determined by the W-put/W-call spread ratio. Since only the W-puts will be exercised when the spot market price appreciates below strike price K_1, the outstanding amount of USD that the central bank is obligated to transact is covered by the USD proceeding from its long position.

Figure 10. Appreciation Dynamic Delta-Hedging Outcomes (W-put/W-call spread: 4)



Notes: The dynamic delta-hedging position is calculated for 100 series for a thirty-day contract. The exchange rate is steadily appreciating over the period to maturity. The W-put/W-call spread ratio is 4. As can be seen, holding a position in both a W-call spread and W-put spread strategy is the least disruptive to the spot market and contributes to countering the persistent appreciation simulated in the market.

The W-call spreads expire out of the money and are not exercised when the spot exchange rate at maturity falls below K_1.[20] The initial purchase position on the first day for the W-call spreads is offset by the subsequent smaller purchases throughout the contract period. Therefore, the central bank is only transacting on the spot market the amount needed to cover its option obligations in the W-spread strategy.

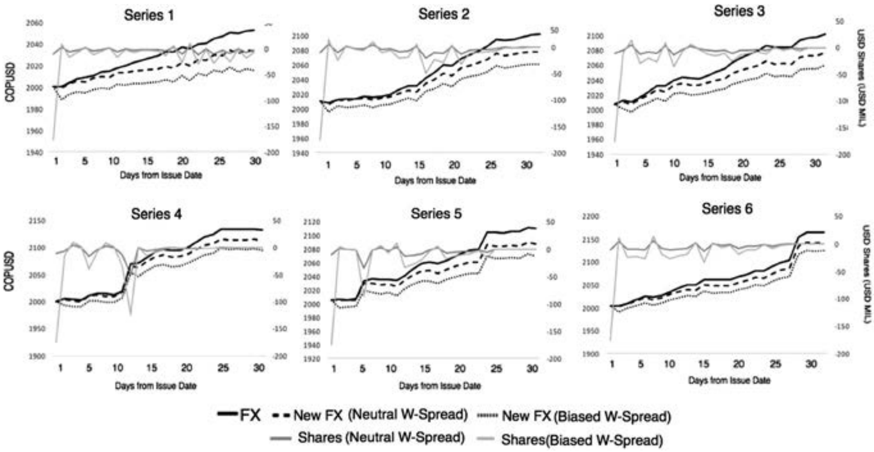
[20] It is important to note that the exercise of each of the puts or calls will be determined by whether the spot exchange rate at maturity is greater than or less than the corresponding strike price. In the scenarios presented here, the spot exchange rate has appreciated below K_1, which is 1,875.

Table 9. End-of-Period Dynamic Delta Costs, Payoffs, and Premiums

	Average Across Series (USD)			
	W-Put/W-Call = 1	**St. Dev.**	**W-Put/W-Call = 4**	**St. Dev.**
End-of-Period USD Transacted	50,082,000	5,910	80,164,000	5,379
Interest Cost	−92,052	4,942	−170,830	5,379
Long Payoff	1,791,700	3,968	3,480,700	6,951
Short Payoff	−895,850	1,984	−1,740,300	3,475
Long Premium	−687,050	1,522	−527,320	1,053
Short Premium	327,940	726	248,070	495
Profit/Cost of Option Strategy	444,688	4,236	1,290,320	4,076
Share of Total	0.44%	0.004%	1.29%	0.004%

Notes: "End-of-Period USD Transacted" represents the cumulative value of daily dynamic delta hedging and interest costs. Each contract size is USD 10,000 and there are 10,000 contracts issued. The table depicts the values for series when the portfolio position is neutral (W-put/W-call spread ratio of 1) as well as for a biased portfolio, with a W-put/W-call spread greater than 1 during a period of appreciation. The calculations reflect those described in the summary table 6. The negative values reflect a cost or outlay of funds for the central bank, whereas the positive values reflect funds acquired by the central bank.

Figure 11. Intervention Impact on COPUSD under Trending Depreciation



Notes: This figure presents a sample of the simulation results for the W-spread strategy. Here, we depict the impact of dynamic delta hedging on the value of the exchange rate under various depreciation scenarios. The top three graphs illustrate persistent depreciation without any shocks. The bottom three graphs illustrate depreciation with a "shock" to the exchange rate. Included are both the neutral strategy (W-put/W-call spread ratio equal to 1) and a biased strategy (W-put/W-call spread ratio equal to 0.25). Adopting the W-strategy allows the central bank to lower volatility while stabilizing the trend.

5.3 Simulation with Intervention Impact on Exchange Rate Movements

After establishing the operations of the W-strategy above, we now present the impact of the W-strategy on exchange rate movements. We consider the following scenarios: persistent depreciation, depreciation with a shock, persistent appreciation, appreciation with a shock, and volatility with no trend. Specifically, we are simulating how dynamic delta hedging of the W-strategy affects the exchange rate. This represents the day-to-day purchases/sales in the spot market conducted by the central bank until the time to maturity of the options bundle.

Figure 11 illustrates the impact of the W-strategy on exchange rate movements under depreciation pressure when there is no intervention impact, when a neutral W-strategy is enacted, and when

Table 10. Volatility for Intervention Impact of W-Strategy under Trending Depreciation

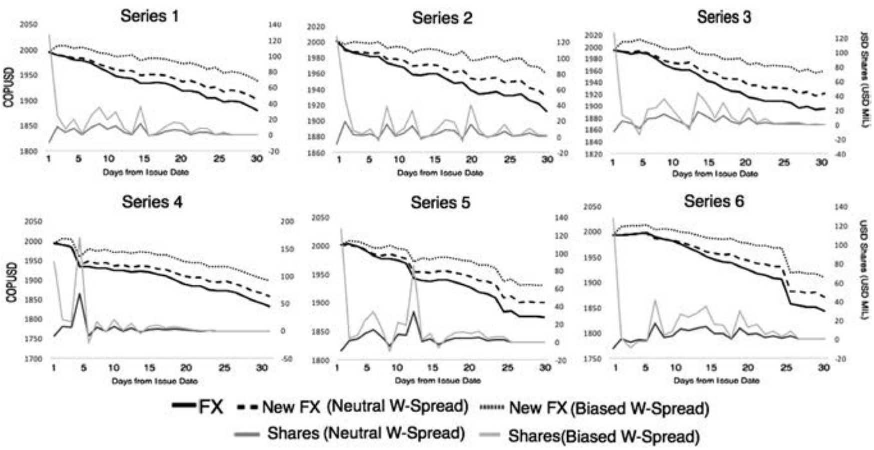
	Series 1	**Series 2**	**Series 3**	**Simulation**
Volatility (No Intervention)	16.76	34.39	29.89	29.85
Volatility (Neutral W-Strategy)	10.61	26.56	21.72	23.14
Volatility Reduction	37%	23%	27%	22%
Volatility (Biased W-Strategy)	8.05	23.15	18.53	20.32
Volatility Reduction	52%	33%	38%	32%
	Series 4	**Series 5**	**Series 6**	**Simulation**
Volatility (No Intervention)	51.69	35.24	49.90	31.18
Volatility (Neutral W-Strategy)	45.31	28.33	42.86	24.87
Volatility Reduction	12%	20%	13%	20%
Volatility (Biased W-Strategy)	41.59	25.17	40.00	21.76
Volatility Reduction	20%	29%	19%	30%

Notes: This table presents the volatility measures of the COPUSD related to the intervntion impacts illustrated in figure 11. The "Simulation" column represents the average values across 100 simulations in each scenario. The volatility reduction percentages represent $1 - \frac{Vol_{Intervention}}{Vol_{NoIntervention}}$. In all cases, the W-strategy is effective in lowering volatility of the COPUSD, which is calculated as the standard deviation of the exchange rate during the time to maturity of the option.

a biased W-strategy is enacted. As can be seen, the trend remains consistent even with the use of the W-strategy, but the volatility of the exchange rate is smoothed. Furthermore, the trend is stabilized when dynamic delta hedging dictates the size of the daily intervention. The depreciation is not as severe when the central bank is buying/selling USD in the spot market to uphold its delta-hedging position. As can be seen in table 10, exchange rate volatility during the time to maturity is lower when the strategy is enacted, and is lowest when the strategy is biased with a stronger position in calls. This holds true even with the presence of a sizable shock in the exchange rate (steep and sudden depreciation).

Figure 12 similarly illustrates the impact of the W-strategy on exchange rate movements under appreciation pressure. The daily position requires the central bank to sell USD under persistent appreciation, as presented in previous graphs. When the impact on the exchange rate is accounted for, the W-strategy once again does not alter the trend of the exchange rate but lowers the volatility and

Figure 12. Intervention Impact on COPUSD under Trending Appreciation



Notes: This figure presents a sample of the simulation results for the W-spread strategy. Here, we depict the impact of dynamic delta hedging on the value of the exchange rate under various appreciation scenarios. The top three graphs illustrate persistent appreciation without any shocks. The bottom three graphs illustrate appreciation with a "shock" to the exchange rate. Included are both the neutral strategy (W-put/W-call spread ratio equal to 1) and a biased strategy (W-put/W-call spread ratio equal to 4). Adopting the W-strategy allows the central bank to lower volatility while stabilizing the trend.

size of the change. In table 11, exchange rate volatility during time to maturity is lowered when the central bank intervenes daily based on the delta-hedging position dictated by the W-strategy. Volatility is lowest when a biased, put-heavy strategy is enacted. Furthermore, as can be seen from figure 12, the trend is stabilized with the daily interventions via dynamic delta hedging.[21]

In figure 13, the exchange rate is moving with no specific trend. Even under this scenario, enacting the W-strategy lowers volatility of the exchange rate. When there is no specific trend and no shock present, the neutral W-strategy provides an intervention position via

[21]It is important to note once again that if changes in the trend are driven by changes in fundamentals, this cannot be changed by W-strategies or any intervention method, but central banks can observe the final composition of the W-spread to obtain important insights from the market participants.

Table 11. Volatility for Intervention Impact of W-Strategy under Trending Appreciation

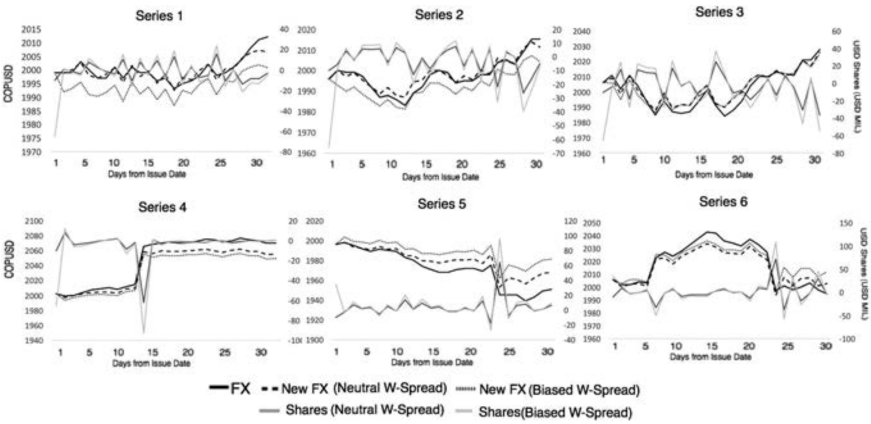
	Series 1	**Series 2**	**Series 3**	**Simulation**
Volatility (No Intervention)	33.95	23.84	35.21	22.91
Volatility (Neutral W-Strategy)	26.93	17.88	26.25	16.35
Volatility Reduction	21%	25%	25%	29%
Volatility (Biased W-Strategy)	19.77	11.01	17.63	11.98
Volatility Reduction	43%	54%	50%	48%
	Series 4	**Series 5**	**Series 6**	**Simulation**
Volatility (No Intervention)	42.90	42.75	51.64	29.45
Volatility (Neutral W-Strategy)	35.80	33.55	41.03	22.91
Volatility Reduction	17%	22%	21%	22%
Volatility (Biased W-Strategy)	29.00	25.94	33.00	18.92
Volatility Reduction	32%	39%	36%	36%

Notes: This table presents the volatility measures of the COPUSD related to the intervntion impacts illustrated in figure 12. The "Simulation" column represents the average values across 100 simulations in each scenario. The volatility reduction percentages represent $1 - \frac{Vol_{Intervention}}{Vol_{NoIntervention}}$. In all cases, the W-strategy is effective in lowering volatility of the COPUSD, which is calculated as the standard deviation of the exchange rate during the time to maturity of the option.

the dynamic delta hedge that lowers volatility more than a biased strategy. This can be seen in the figure as well as in table 12. When a shock occurs during the time to maturity, the biased W-strategy gives the central bank a stronger position in the spot market via dynamic delta hedging and therefore is more effective in lowering volatility. Both the neutral and biased strategies lead to lower volatility in the exchange rate.

Once more, it is important to note that intervention following the delta-hedging position does not permanently alter the foreign exchange reserve balance. As discussed previously, at maturity, the central bank will have accumulated a foreign currency balance to satisfy its obligations as the options are executed. The net effect on reserve balances will therefore be very close to zero. Therefore, dynamic delta hedging of this strategy allows the central bank to effectively intervene in the spot market daily where the intervention position is based on market forces without depleting or over-accumulating foreign exchange reserves.

Figure 13. Intervention Impact on COPUSD under No Trend



Notes: This figure presents a sample of the simulation results for the W-spread strategy. Here, we depict the impact of dynamic delta hedging on the value of the exchange rate under scenarios where the exchange rate does not follow a specific trend. The top three graphs illustrate the COPUSD without any shocks. The bottom three graphs illustrate the exchange rate reaction with a "shock." Included are both the neutral strategy (W-put/W-call spread ratio equal to 1) and a biased strategy (W-put/W-call spread ratio equal to 4 or 0.25, depending on the shock). Adopting the W-strategy allows the central bank to lower volatility while stabilizing the trend.

6. Conclusion

Foreign exchange intervention as a means to smooth volatility and protect the economy from external shocks is an underlying concern for many emerging market policymakers. Many now struggle with finding strategies that would limit volatility while allowing them to maintain flexible exchange rates. Currently, spot market purchase/sale of USD to limit volatility is an imperfect solution to this issue because the intervention may overshoot/undershoot its intended goal and set off speculative activity. This paper has argued that the use of currency options may be a stronger and more market-driven approach to foreign exchange interventions.

In past literature, currency options have been considered as a potential tool for central bank currency market intervention, but those strategies have fallen short because they considered only one

Table 12. Volatility for Intervention Impact of W-Strategy under No Trend

	Series 1	Series 2	Series 3	Simulation
Volatility (No Intervention)	4.55	7.99	12.50	5.56
Volatility (Neutral W-Strategy)	3.62	6.85	10.37	4.15
Volatility Reduction	20%	14%	17%	25%
Volatility (Biased W-Strategy)	4.00	6.80	10.48	4.89
Volatility Reduction	12%	15%	16%	12%
	Series 4	**Series 5**	**Series 6**	**Simulation**
Volatility (No Intervention)	32.36	18.73	16.97	13.47
Volatility (Neutral W-Strategy)	27.42	12.88	12.67	11.06
Volatility Reduction	15%	31%	18%	22%
Volatility (Biased W-Strategy)	26.10	10.45	11.68	9.70
Volatility Reduction	19%	44%	31%	28%

Notes: This table presents the volatility measures of the COPUSD related to the intervntion impacts illustrated in figure 12. The "Simulation" column represents the average values across 100 simulations in each scenario. The volatility reduction percentages represent $1 - \frac{Vol_{Intervention}}{Vol_{NoIntervention}}$. In all cases, the W-strategy is effective in lowering volatility of the COPUSD, which is calculated as the standard deviation of the exchange rate during the time to maturity of the option.

side of the market (call or put) or only one position (short or long). With the W-spread strategy, the central bank is operating in both sides of market with more than one position. The intervention still occurs in the spot market, but it is now driven by market forces that dictate the size of the purchase/sale of USD on a daily basis through dynamic delta hedging, as well as at contract maturity. The portfolio mix of calls and puts can be altered by the central bank or change based on market expectations, making the central bank's position more responsive to the market. A major secondary benefit to this strategy, and the use of options by central banks in general, is the establishment or deepening of risk markets. In many emerging market economies, local import/export businesses would benefit from access to options in the local currency, yet these tools make up only a small share of the total foreign exchange tools currently available (BIS 2016).

The goal of the analysis presented in this paper has been to lay the foundation for a serious discussion on the implementation of currency options as a central bank policy tool. We find that with an alternative option trading strategy, such as the W-spread strategy, the central bank can reach its goal of limiting exchange rate volatility and smoothing the exchange rate trend with a market-driven intervention approach.

Appendix. Offsetting Position of Market Participants

For every transaction in the options market the central bank engages in, there is an offsetting position by a market participant that must purchase or sell the option. It is important to understand what happens, in terms of delta hedging, on the other side of the market when the central bank is engaging in the W-spread proposed in this paper. Traders can choose to hedge part or all of their net portfolio position. Since hedging can be costly and not all market participants have the same motives to use the options markets,[22] not all traders will hedge their entire portfolio position, which has important implications for our analysis.

The hedging of the short position is what may exacerbate the adverse movements in the exchange rates. If we start by assuming that when the central bank is holding a net long position through the W-spread, there is only one trader that is holding all of the offsetting options, which implies that this trader would be in a net short portfolio position, making it feasible that this trader may engage in delta hedging. His delta hedging increases volatility and can potentially modify the exchange rate trend, which is problematic for the central bank. However, the likelihood of one trader holding all of the central bank's offsetting position is very small, and it is not advisable for the central bank to allow such a situation to materialize. On the other hand, for individual hedgers and speculators, it is costly to hedge their entire position in the options market. Moreover, some may be using the option itself as the risk-management tool of choice. Therefore, the hedging activity of traders may not match one for one the hedging activity of the central bank.

Tables 13 to 15 present the total USD that is purchased and sold by central banks and market participants when the central bank is

[22] For example, exporters and importers in general are not interested in delta hedging their positions. They use options to eliminate exchange rate uncertainty at maturity.

Table 13. Central Bank and Traders' Hedging Positions with 100 Percent Hedge

	Net USD Purchased by Central Bank						Net USD Purchased by Traders						Net USD Transacted by Both
	Calls			Puts			Calls			Puts			
Ex. Rate	Long (K_1)	Long (K_3)	Short (K_2)	Long (K_1)	Long (K_3)	Short (K_2)	Short (K_1)	Short (K_3)	Long (K_2)	Short (K_1)	Short (K_3)	Long (K_2)	Net USD
COPUSD	USD	USD	USD	USD	USD	USD	100%	100%	100%	100%	100%	100%	
2044.00	−5,856	−5,042	5,451	4,144	4,958	−4,549	5,856	5,042	−5,451	−4,144	−4,958	4,549	0
2050.00	−494	−498	499	−494	−498	499	494	498	−499	494	498	−499	0
2053.00	−231	−230	232	−231	−230	232	231	230	−232	231	230	−232	0
2054.00	−66	−55	61	−66	−55	61	66	55	−61	66	55	−61	0
2054.00	−45	−32	39	−45	−32	39	45	32	−39	45	32	−39	0
2060.00	−489	−518	507	−489	−518	507	489	518	−507	489	518	−507	0
2066.00	−444	−484	466	−444	−484	466	444	484	−466	444	484	−466	0
2076.00	−627	−723	678	−627	−723	678	627	723	−678	627	723	−678	0
2076.00	−77	−78	79	−77	−78	79	77	78	−79	77	78	−79	0
2085.00	−524	−646	586	−524	−646	586	524	646	−586	524	646	−586	0
2093.00	−359	−467	413	−359	−467	413	359	467	−413	359	467	−413	0
2099.00	−214	−292	252	−214	−292	252	214	292	−252	214	292	−252	0
2106.00	−217	−316	264	−217	−316	264	217	316	−264	217	316	−264	0
2111.00	−122	−187	152	−122	−187	152	122	187	−152	122	187	−152	0
2114.00	−61	−97	78	−61	−97	78	61	97	−78	61	97	−78	0
2119.00	−69	−118	91	−69	−118	91	69	118	−91	69	118	−91	0
2126.00	−56	−106	78	−56	−106	78	56	106	−78	56	106	−78	0
2135.00	−32	−68	47	−32	−68	47	32	68	−47	32	68	−47	0
2141.00	−10	−25	16	−10	−25	16	10	25	−16	10	25	−16	0

(*continued*)

Table 13. (Continued)

	Net USD Purchased by Central Bank						Net USD Purchased by Traders						Net USD Transacted by Both
	Calls			Puts			Calls			Puts			
Ex. Rate	**Long (K_1)**	**Long (K_3)**	**Short (K_2)**	**Long (K_1)**	**Long (K_3)**	**Short (K_2)**	**Short (K_1)**	**Short (K_3)**	**Long (K_2)**	**Short (K_1)**	**Short (K_3)**	**Long (K_2)**	**Net USD**
COPUSD	**USD**	**USD**	**USD**	**USD**	**USD**	**USD**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	
2144.00	−3	−9	6	−4	−9	6	3	9	−6	4	9	−6	0
2149.00	−2	−6	3	−2	−6	3	2	6	−3	2	6	−3	0
2156.00	−1	−2	1	−1	−2	1	1	2	−1	1	2	−1	0
2162.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2166.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2175.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2182.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2188.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2189.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2195.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2196.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2196.00	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	−9,999	−9,999	9,999	0	1	−1	9,999	9,999	−9,999	0	−1	1	0

Notes: This table illustrates the spot market position of the central bank and traders during daily dynamic delta hedging of a W-spread when there is persistent depreciation. It represents the net hedging strategy where each contract in the strategy is for USD 10,000. Here, the traders are hedging 100 percent of their position.

Table 14. Central Bank and Traders' Hedging Positions with 50 Percent Hedge

	Net USD Purchased by Central Bank						Net USD Purchased by Traders						Net USD Transacted by Both
	Calls			Puts			Calls			Puts			
Ex. Rate	Long (K_1)	Long (K_3)	Short (K_2)	Long (K_1)	Long (K_3)	Short (K_2)	Short (K_1)	Short (K_3)	Long (K_2)	Short (K_1)	Short (K_3)	Long (K_2)	Net USD
COPUSD	USD	USD	USD	USD	USD	USD	50%	50%	50%	50%	50%	50%	
2044.00	−5,856	−5,042	5,451	4,144	4,958	−4,549	2,928	2,521	−2,726	−2,072	−2,479	2,275	−447
2050.00	−494	−498	499	−494	−498	499	247	249	−250	247	249	−250	−493
2053.00	−231	−230	232	−231	−230	232	116	115	−116	116	115	−116	−229
2054.00	−66	−55	61	−66	−55	61	33	28	−31	33	28	−31	−60
2054.00	−45	−32	39	−45	−32	39	23	16	−20	23	16	−20	−38
2060.00	−489	−518	507	−489	−518	507	245	259	−254	245	259	−254	−500
2066.00	−444	−484	466	−444	−484	466	222	242	−233	222	242	−233	−462
2076.00	−627	−723	678	−627	−723	678	314	362	−339	314	362	−339	−672
2076.00	−77	−78	79	−77	−78	79	39	39	−40	39	39	−40	−76
2085.00	−524	−646	586	−524	−646	586	262	323	−293	262	323	−293	−584
2093.00	−359	−467	413	−359	−467	413	180	234	−207	180	234	−207	−413
2099.00	−214	−292	252	−214	−292	252	107	146	−126	107	146	−126	−254
2106.00	−217	−316	264	−217	−316	264	109	158	−132	109	158	−132	−269
2111.00	−122	−187	152	−122	−187	152	61	94	−76	61	94	−76	−157
2114.00	−61	−97	78	−61	−97	78	31	49	−39	31	49	−39	−80
2119.00	−69	−118	91	−69	−118	91	35	59	−46	35	59	−46	−96
2126.00	−56	−106	78	−56	−106	78	28	53	−39	28	53	−39	−84
2135.00	−32	−68	47	−32	−68	47	16	34	−24	16	34	−24	−53
2141.00	−10	−25	16	−10	−25	16	5	13	−8	5	13	−8	−19

(*continued*)

Table 14. (Continued)

	Net USD Purchased by Central Bank						Net USD Purchased by Traders						Net USD Transacted by Both
	Calls			Puts			Calls			Puts			
Ex. Rate	**Long (K_1)**	**Long (K_3)**	**Short (K_2)**	**Long (K_1)**	**Long (K_3)**	**Short (K_2)**	**Short (K_1)**	**Short (K_3)**	**Long (K_2)**	**Short (K_1)**	**Short (K_3)**	**Long (K_2)**	**Net USD**
COPUSD	**USD**	**USD**	**USD**	**USD**	**USD**	**USD**	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	
2144.00	−3	−9	6	−4	−9	6	2	5	−3	2	5	−3	−7
2149.00	−2	−6	3	−2	−6	3	1	3	−2	1	3	−2	−5
2156.00	−1	−2	1	−1	−2	1	1	1	−1	1	1	−1	−2
2162.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2166.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2175.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2182.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2188.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2189.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2195.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2196.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2196.00	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	−9,999	−9,999	9,999	0	1	−1	5,000	5,000	−5,000	0	−1	1	−5,000

Notes: This table illustrates the spot market position of the central bank and traders during daily dynamic delta hedging of a W-spread when there is persistent depreciation. It represents the net hedging strategy where each contract in the strategy is for USD 10,000. Here, the traders are hedging 50 percent of their position.

Table 15. Central Bank and Traders' Hedging Positions with 10 Percent Hedge

	Net USD Purchased by Central Bank						Net USD Purchased by Traders						Net USD Transacted by Both
	Calls			Puts			Calls			Puts			
Ex. Rate	Long (K_1)	Long (K_3)	Short (K_2)	Long (K_1)	Long (K_3)	Short (K_2)	Short (K_1)	Short (K_3)	Long (K_2)	Short (K_1)	Short (K_3)	Long (K_2)	Net USD
COPUSD	USD	USD	USD	USD	USD	USD	10%	10%	10%	10%	10%	10%	
2044.00	−5,856	−5,042	5,451	4,144	4,958	−4,549	586	504	−545	−414	−496	455	−805
2050.00	−494	−498	499	−494	−498	499	49	50	−50	49	50	−50	−887
2053.00	−231	−230	232	−231	−230	232	23	23	−23	23	23	−23	−412
2054.00	−66	−55	61	−66	−55	61	7	6	−6	7	6	−6	−108
2054.00	−45	−32	39	−45	−32	39	5	3	−4	5	3	−4	−68
2060.00	−489	−518	507	−489	−518	507	49	52	−51	49	52	−51	−900
2066.00	−444	−484	466	−444	−484	466	44	48	−47	44	48	−47	−832
2076.00	−627	−723	678	−627	−723	678	63	72	−68	63	72	−68	−1,210
2076.00	−77	−78	79	−77	−78	79	8	8	−8	8	8	−8	−137
2085.00	−524	−646	586	−524	−646	586	52	65	−59	52	65	−59	−1,051
2093.00	−359	−467	413	−359	−467	413	36	47	−41	36	47	−41	−743
2099.00	−214	−292	252	−214	−292	252	21	29	−25	21	29	−25	−457
2106.00	−217	−316	264	−217	−316	264	22	32	−26	22	32	−26	−484
2111.00	−122	−187	152	−122	−187	152	12	19	−15	12	19	−15	−283
2114.00	−61	−97	78	−61	−97	78	6	10	−8	6	10	−8	−144
2119.00	−69	−118	91	−69	−118	91	7	12	−9	7	12	−9	−173
2126.00	−56	−106	78	−56	−106	78	6	11	−8	6	11	−8	−151
2135.00	−32	−68	47	−32	−68	47	3	7	−5	3	7	−5	−95
2141.00	−10	−25	16	−10	−25	16	1	3	−2	1	3	−2	−34

(*continued*)

Table 15. (Continued)

	Net USD Purchased by Central Bank						Net USD Purchased by Traders						Net USD Transacted by Both
	Calls			Puts			Calls			Puts			
Ex. Rate	**Long (K_1)**	**Long (K_3)**	**Short (K_2)**	**Long (K_1)**	**Long (K_3)**	**Short (K_2)**	**Short (K_1)**	**Short (K_3)**	**Long (K_2)**	**Short (K_1)**	**Short (K_3)**	**Long (K_2)**	**Net USD**
COPUSD	**USD**	**USD**	**USD**	**USD**	**USD**	**USD**	**10%**	**10%**	**10%**	**10%**	**10%**	**10%**	
2144.00	−3	−9	6	−4	−9	6	0	1	−1	0	1	−1	−12
2149.00	−2	−6	3	−2	−6	3	0	1	0	0	1	0	−9
2156.00	−1	−2	1	−1	−2	1	0	0	0	0	0	0	−4
2162.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2166.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2175.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2182.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2188.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2189.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2195.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2196.00	0	0	0	0	0	0	0	0	0	0	0	0	0
2196.00	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	−9,999	−9,999	9,999	0	1	−1	1,000	1,000	−1,000	0	0	0	−8,999

Notes: This table illustrates the spot market position of the central bank and traders during daily dynamic delta hedging of a W-spread when there is persistent depreciation. It represents the net hedging strategy where each contract in the strategy is for USD 10,000. Here, the traders are hedging 10 percent of their position.

hedging 100 percent of its net portfolio position in the W-spread, and the traders are hedging 100, 50, and 10 percent, respectively of their offsetting W-spread positions. In the examples presented below, we assume that the COPUSD is depreciating, and that the hedging position (or spot market intervention driven by the hedging position) does not directly affect the movement of the exchange rate in this simulation. This assumption is used simply to convey the positions the delta hedge would create in the spot market. Under the depreciationary pressure, all calls are exercised, while the puts expire without exercise. The delta hedging therefore nets to 10,000 for each of the call positions and 0 for each of the put positions.

As can be seen in table 13, if both parties engage in 100 percent delta hedging of their portfolios, then the hedging activity in the spot market between the central bank and traders cancel each other out. If traders hedge anything less than 100 percent of their portfolio, the central bank's hedging activity creates stabilizing transactions on the spot market to complement their intended intervention goals. If traders hedge only 50 percent of their portfolio, as seen in table 14, then there is a net sale of USD on the spot market between the traders and the central bank. Finally, if traders hedge only 10 percent of their portfolio, the net position in the spot market is a sale of USD 8,999, as seen in table 15. Therefore, if the net offsetting position by market participants is hedged by anything less than 100 percent, the delta-hedging activity of the central bank provides a spot market intervention strategy that complements the goals of curbing drastic movements of the exchange rate.

It is possible to assume that in fact the offsetting position would not be hedged 100 percent, since the only agents interested in dynamic delta hedging would be market markets and large currency traders. Local import/export business and multinationals use the option itself as a hedge. As a proxy, we can turn to the growth in forward contracts. According to the Triennial Foreign Exchange Market Survey conducted by the Bank for International Settlements, the share of options to total foreign exchange transactions in emerging market economies has remained steady at 2.5 percent since 1998, which may be partially due to the shallowness of this market in these economies. On the other hand, the use of forwards has increased from 7 percent to 10 percent of total foreign exchange transactions, representing growth of 48 percent. By design, forward contracts are not hedged and are used by non-market makers as a hedge in and of themselves, as the option would be in our proposed strategy. Therefore, if the central bank makes options more readily available to these players by operating in and building up this market, it is possible to assume that the share of options that would be dynamically delta hedged would be less than 100 percent.

References

Adler, G., and C. Tovar. 2011. "Foreign Exchange Intervention: A Shield Against Appreciation Winds?" IMF Working Paper No. 11/165.

Akinci, O., O. Culha, U. Ozlale, and G. Sahinbeyoglu. 2006. "The Effectiveness of Foreign Exchange Intervention Under a Floating Exchange Rate Regime for the Turkish Economy: Post-Crisis Period Analysis." *Applied Economics* 38 (12): 1371–88.

Archer, D. 2005. "Foreign Exchange Market Intervention: Methods and Tactics." *BIS Papers* 24: 40–55.

Bank for International Settlements. 2016. "Triennial Central Bank Survey of Foreign Exchange and OTC Derivatives Markets in 2016." Bank for International Settlements Triennial Survey.

Breuer, P. 1999. "Central Bank Participation in Currency Options Markets." IMF Working Paper No. 99/140.

Caballero, R. 2003. "On the International Financial Architecture: Insuring Emerging Markets." NBER Working Paper No. 9570.

Chen, Z., ed. 1998. *Currency Options and Exchange Rate Economics.* World Scientific Publishing Co.

Daude, C., E. Levy Yeyati, and A. Nagengast. 2014. "On the Effectiveness of Exchange Rate Interventions in Emerging Markets." Working Paper No. 324, OECD Development Centre.

DeRosa, D. F. 2011. *Options on Foreign Exchange.* 3rd Edition. Wiley.

Domanski, D., E. Kohlscheen, and R. Moreno. 2016. "Foreign Exchange Market Intervention in EMEs: What Has Changed?" *BIS Quarterly Review* (September): 65–79.

Egbert, B. 2007. "Central Bank Interventions, Communication and Interest Rate Policy in Emerging European Economies." *Journal of Comparative Economics* 35 (2): 387–413.

Fratzscher, M., O. Gloede, L. Menkho, L. Sarno, and T. Stoher. 2015. "When is Foreign Exchange Intervention Effective? Evidence from 33 Countries." Discussion Paper No. 1518, DIW Berlin.

Garber, P. 1994. "Foreign Exchange Hedging with Synthetic Options and the Interest Rate Defense of a Fixed Exchange Rate Regime." IMF Working Paper No. 94/151.

Guinigundo, D. 2013. "A Note on the Effectiveness of Intervention in the Foreign Exchange Market: The Case of the Philippines."' *BIS Papers* 73: 263–77.

Hull, J. C. 2012. *Risk Management and Financial Institutions*. 3rd Edition. John Wiley and Sons, Inc.

Keefe, H. G., and E. Rengifo. 2015. "Options and Central Bank Currency Market Intervention: The Case of Colombia." *Emerging Markets Review* 23 (June): 1–25.

Leon, H., and O. H. Williams. 2012. "Effectiveness of Intervention in a Small Emerging Market: An Event Study Approach." *Applied Financial Economics* 22 (21): 1811–20.

Malz, A. 1995. "Currency Option Markets and Exchange Rates: A Case Study of the US dollar in March 1995." *Current Issues in Economics and Finance* (Federal Reserve Bank of New York) 1 (July).

Mihaljek, D., and F. Packer. 2010. "Derivatives in Emerging Markets." *BIS Quarterly Review* (December): 43–58.

Nedeljkovic, M., and C. Saborowski. 2017. "The Relative Effectiveness of Spot and Derivatives Based Intervention: The Case of Brazil." IMF Working Paper No. 17/11.

Wiseman, J. D. 1999. "Using Options to Stabilise FX: A New Exchange Rate Mechanism." Paper based on Sections 2 and 3 of Special Paper No. 84, Financial Markets Group of the London School of Economics.

Zapatero, F., and L. F. Reverter. 2003. "Exchange Rate Intervention with Options." *Journal of International Money and Finance* 22 (2): 289–306.

External Shocks, Banks, and Optimal Monetary Policy: A Recipe for Emerging Market Central Banks*

Yasin Mimir[a] and Enes Sunel[b]
[a]Norges Bank
[b]Sunel & Sunel Law Firm

We document that the 2007–09 global financial crisis exposed emerging market economies to an adverse feedback loop of capital outflows, depreciating exchange rates, deteriorating balance sheets, rising credit spreads, and falling real economic activity. We account for these empirical findings by building a New Keynesian DSGE model of a small open economy with a banking sector that has access to both domestic and foreign funding. Using the calibrated model, we investigate optimal, simple, and implementable interest rate rules that respond to domestic/external financial variables alongside inflation and output. The Ramsey-optimal policy is used as a benchmark. We find that optimized interest rate rules respond to the real exchange rate, asset prices, and lending spreads.

*We would like to thank the Editor, two anonymous referees, Leonardo Gambacorta, Nobuhiro Kiyotaki, Giovanni Lombardo, Hyun Song Shin, Philip Turner, the seminar participants at the Bank for International Settlements, Norges Bank, the Georgetown Center for Economic Research Biennial Conference 2015, the CBRT-BOE Joint Workshop 2015 on "The International Monetary and Financial System — Long-term Challenges, Short-term Solutions," the 21st International Conference on Computing in Economics and Finance, the 11th World Congress of the Econometric Society, and the 47th Money, Macro and Finance Research Group Annual conference for their helpful comments and suggestions. This paper circulated earlier under the title "External Shocks, Banks and Optimal Monetary Policy in an Open Economy." Yasin Mimir completed this project while visiting the Bank for International Settlements under the Central Bank Research Fellowship program. The views expressed in this paper are those of the authors only and do not necessarily reflect the views of Norges Bank or of the Bank for International Settlements (BIS). The usual disclaimer applies. Corresponding author: Yasin Mimir, Norges Bank, Monetary Policy Department, Bankplassen 2, 0151 Oslo, Norway; Tel.: +4722316811; E-mail: yasin.mimir@norges-bank.no; Personal homepage: http://www.yasinmimir.com.

Furthermore, augmented interest rate policy usually takes a stronger anti-inflationary stance when monetary policy maintains financial stability. A jointly optimized mix of reserve requirements that smooth credit spreads and a standard Taylor-type interest rate rule dominates augmented interest rate rules under country risk premium shocks.

JEL Codes: E44, E52, F41.

1. Introduction

The 2007–09 global financial crisis exposed emerging market economies (EMEs) to an adverse feedback loop of capital outflows, depreciating exchange rates, deteriorating balance sheets, rising credit spreads, and falling real economic activity. Furthermore, the unconventional response of advanced economy policymakers to the crisis caused EMEs to sail in uncharted waters from a monetary policymaking perspective. These adverse developments revitalized the previous debate about whether central banks should pay attention to domestic or external financial variables over and above their effects on inflation or real economic activity. Consequently, the lean-against-the-wind (LAW) policies—defined as augmented Taylor-type monetary policy rules that additionally respond to domestic or external financial variables—are now central to discussions in both academic and policy circles.[1] This debate is even more pronounced in EMEs in which banks are the main source of credit extension and their sizable reliance on non-core debt amplifies the transmission of external shocks, threatening both price and financial stability objectives.[2] In this regard, this paper aims to provide a recipe for EME central banks in rethinking interest rate policy determination.

We study optimal monetary policy in an open economy with financial market imperfections in the presence of both domestic and external shocks. Using a canonical New Keynesian DSGE model of a small open economy augmented by a banking sector that has access

[1]See the discussion in Angelini, Neri, and Panetta (2011).

[2]The median share of bank credit in total credit to the non-financial sector in EMEs was 87 percent in 2013, while the median share of non-core debt in total liabilities was 33 percent. For more details, see Ehlers and Víllar (2015). For other related discussions, see Obstfeld (2015) and Rey (2015).

to both domestic and foreign funds, we investigate the quantitative performances of optimal, simple, and implementable LAW-type interest rate rules relative to a Ramsey-optimal monetary policy rule. We follow the definition of Schmitt-Grohé and Uribe (2007) in constructing such rules that respond to easily observable macroeconomic variables while preserving the determinacy of equilibrium. We consider a small number of targets among a wide range of variables that are arguably important for policymaking. In particular, we look at the level of bank credit, asset prices, credit spreads, the U.S. interest rate, and the real exchange rate as additional inputs to policy. We then compare these optimal LAW-type Taylor rules with standard optimized Taylor rules (with and without interest rate smoothing).

Our model builds on Galí and Monacelli (2005). The main departure from their work is that we introduce an active banking sector as in Gertler and Kiyotaki (2011). In this class of models, financial frictions require banks to collect funds from external sources while limiting their demand for debt because of an endogenous leverage constraint resulting from a costly enforcement problem. This departure generates a financial accelerator mechanism by which the balance sheet fluctuations of banks affect real economic activity. Our model differs from that of Gertler and Kiyotaki (2011) in that it replaces interbank borrowing with foreign debt in an open-economy setup. Consequently, the endogenous leverage constraint of bankers is additionally affected by fluctuations in the exchange rate.

We assume that frictions between banks, on one side, and their domestic and foreign creditors, on the other side, are asymmetric. Specifically, domestic depositors are assumed to be more efficient than international investors in recovering assets from banks in case of bankruptcy. This makes foreign debt more risky, creates a wedge between the real costs of domestic and foreign debt, and hence violates the uncovered interest parity (UIP) condition.[3] This

[3]We empirically illustrate in the bottom-left panel of figure 1 that, with the exception of the period 2010:Q2–2011:Q3, credit spreads on foreign debt are larger than credit spreads on domestic deposits. This implies that domestic deposit rates are higher than foreign deposit rates. This regularity dates back to 2002:Q4 for the average EME in our sample. For a detailed survey on the violation of the UIP, see Engel (2014b). For theoretical contributions on domestic funding premium, see Broner et al. (2014) and Fornaro (2015).

key ingredient gives us the ability to empirically match the liability structure of domestic banks (which is defined as the share of noncore liabilities in total bank liabilities) and analyze changes in this measure in response to external shocks. Lastly, our model incorporates various real rigidities that generally form part of medium-scale DSGE models such as those studied by Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007). In particular, the model's empirical fit is improved by features such as habit formation in consumption, variable capacity utilization, and investment adjustment costs.

First, we analytically derive the intratemporal and intertemporal wedges in our model economy and compare them with a first-best flexible-price closed-economy model to better understand the policy tradeoffs that the Ramsey planner faces in response to shocks. We show that the distortions in the intratemporal wedge are mainly driven by the variations in the inflation rate and the real exchange rate induced by monopolistic competition, price stickiness, home bias, and incomplete exchange rate pass-through. At the same time, the distortions in the intertemporal wedge are mainly driven by the variations in the lending spreads over the costs of domestic and foreign deposits together with those in the real exchange rate induced by financial market imperfections and open-economy features.

We then conduct our quantitative analysis under five different types of shocks that might be most relevant for optimal policy prescription in EMEs. The first two of these are total factor productivity and government spending, which we label as domestic shocks. The remaining three are the country borrowing premium, the U.S. interest rate, and export demand, which we label as external shocks.[4] Finally, we also analyze optimal policy in an economy driven jointly by all of these shocks given that it might be difficult for the monetary authority to perfectly disentangle the different sources of business cycle movements while designing its policy.

[4]A shock to a country's borrowing premium can be justified by the reduction in the global risk appetite driven by the collapse of Lehman Brothers in September 2008 or the taper tantrum of May 2013. A shock to the U.S. interest rate can be justified by the accommodative monetary stance of the Federal Reserve in the aftermath of the crisis or the policy normalization that was expected in late 2015.

We find that the Ramsey-optimal policy substantially reduces relative volatilities of inflation, markup, the real exchange rate, and loan–deposits interest rate spreads, compared with a decentralized economy, in which interest rate policy is a standard Taylor rule calibrated to the data. Moreover, in comparison with the optimized simple rules, the Ramsey-optimal policy produces fairly smaller degrees of volatility in inflation and the real exchange rate while implying relatively larger degrees of volatility in credit spreads and asset prices. High volatility in credit spreads hints that the Ramsey planner weighs distortions resulting from price dispersion and exchange rate fluctuations more, compared with stabilizing inefficiencies resulting from credit frictions. Increased volatility in asset prices, on the other hand, relates to the mechanism discussed by Faia and Monacelli (2007) that the constrained planner is adjusting asset prices to bring fluctuations in investment closer to efficient fluctuations. This is mainly because asset prices effectively work as a procyclical tax on investment under adjustment costs. The rationale behind this is similar to that in Arseneau and Chugh (2012) in which the Ramsey planner increases the volatility of labor income tax rate under labor market frictions to bring fluctuations in employment closer to the efficient fluctuations.

Under country risk premium shocks, the real exchange rate (RER) augmented rule which displays an aggressive and positive response to fluctuations in the real exchange rate and only mild responses to inflation and output variations implies the largest welfare among all optimized augmented Taylor rules. The implied welfare loss of this policy vis-à-vis the Ramsey-optimal policy is 0.0015 percent in terms of changes that compensate variation in consumption. This suggests that addressing the financial channel for an EME central bank is crucial (by which exchange rate depreciation hurts the balance sheets of domestic borrowers who face currency mismatch, leading them to curb domestic demand) rather than leaving adjustments to the trade channel that operates via price competitiveness as empirically documented by Kearns and Patel (2016). Since the central bank is already fighting the pass-through aggressively, it is not deemed useful to take a strong anti-inflationary stance under this policy. This finding is linked to the insights discussed by Monacelli (2005, 2013) that under incomplete exchange rate pass-through, fluctuations in the exchange rate operate as endogenous cost-push shocks which optimal policy pays more attention to relative to price stability concerns.

Our results confirm the findings of Faia and Monacelli (2007) that an easing in the policy rate gets the dynamics of investment closer to efficient fluctuations in response to a favorable shock. To that end, we find that optimal policy calls for a negative response to asset prices together with a moderate anti-inflationary stance. The welfare cost implied by this policy rule is 0.0021 percent against the Ramsey policy. We find that the credit-spread-augmented Taylor rule achieves a level of welfare very close to that of the asset-price-augmented Taylor rule (the implied cost is 0.0026 percent). Interest rate policy features an LAW role in this case because credit spreads are countercyclical and the optimized augmented rule calls for an easing in bad times.

An optimized standard Taylor rule calls for a much milder anti-inflationary stance than those obtained under either the asset-price- or the credit-spread-augmented rules, and it is sub-optimal. The reason as to why an optimized standard Taylor rule features a milder inflation response is due to the fact that in response to adverse external shocks (which already raise the cost of foreign debt), a strong anti-inflationary stance of interest rate policy without any financial stabilization objective would hurt bank balance sheets even more by increasing the cost of domestic deposits. Moreover, since this rule does not have any financial stabilization objective, it displays higher welfare costs than the asset-price-augmented or the credit-spread-augmented rules. Therefore, we show that using an augmented policy rule with financial stability considerations allows the central bank to take a stronger anti-inflationary stance in line with the insights of Aoki, Benigno, and Kiyotaki (2016).

When all shocks are switched on, we find that the asset-price-augmented rule achieves the highest welfare among alternative optimal simple rules. The welfare cost of implementing this policy relative to the Ramsey-optimal policy rule is 0.0013 percent. Our findings are broadly in line with the case of external shocks, in which responding to credit spreads or the exchange rate is welfare superior to implementing an optimal standard Taylor rule. We also consider monetary policy responses to the U.S. interest rates motivated by the idea that domestic policy rates in EMEs might partly be driven by changes in the U.S. interest rates over and above what domestic factors would imply. The model suggests that it is optimal to positively respond to the U.S. interest rates in line with the empirical findings and discussions of Takáts and Vela (2014) and Hofmann and Takáts (2015). Although this policy rule dominates an optimal standard Taylor rule, it produces a larger welfare cost than those implied by the RER-, asset-price- or credit-spread-augmented interest rate policies.

Using the short-term interest rate for LAW purposes might be difficult should hitting multiple stabilization goals necessitate different trajectories for the single policy tool. In this respect, Shin (2013) and Chung et al. (2014) emphasize the usefulness of liability-based macroprudential policy tools alongside conventional monetary policy. To contemplate on those issues, we operationalize reserve requirements as a policy rule that aims to smooth out fluctuations in credit spreads in addition to conventional interest rate policy. We then examine whether an optimized *mix* of these two tools can compete with an optimized *augmented* interest rate rule in maximizing household welfare. We find that optimal reserve requirement policy exhibits LAW, as it features a negative response to credit spreads. In addition, such a policy mix is found to produce welfare costs that are even smaller than those implied by the RER-augmented interest rate policy under country risk premium shocks.

1.1 Related Literature

This paper is related to a vast body of literature on the optimality of responding to financial variables. In closed-economy frameworks, Faia and Monacelli (2007) use a New Keynesian model with agency costs to argue that responding negatively to asset prices with a Taylor-type interest rate rule is welfare improving. Cúrdia and Woodford (2010) find that it is optimal to respond to credit spreads under financial disturbances in a model with costly financial intermediation. Gilchrist and Zakrajšek (2011) show that a spread-augmented Taylor rule smooths fluctuations in real and financial variables in the Bernanke, Gertler, and Gilchrist (1999) model. Hirakata, Sudo, and Ueda (2013) and Gambacorta and Signoretti (2014) consider frameworks with an explicit and simultaneous modeling of non-financial firms and banks balance sheets. The former study shows that a spread-augmented Taylor rule stabilizes the adverse effects of shocks that widen credit spreads, while the latter paper shows that responding to asset prices entails stabilization benefits even in response to supply side shocks. Notarpietro and Siviero (2015) investigate whether it is welfare improving to respond to house price movements using the Iacoviello and Neri (2010) model with housing assets and collateral constraints. Angeloni and Faia (2013) suggest that smoothing movements in asset prices in conjunction with capital requirements is welfare improving relative to simple policy rules in a New Keynesian model with risky banks. Angelini, Neri, and Panetta (2011) show that macroprudential policy instruments, such as capital requirements and loan-to-value ratios, are effective in response to financial shocks. Mimir, Taşkın, and Sunel (2013) illustrate that countercyclical reserve requirements that respond to credit growth have desirable stabilization properties. We differ from these papers by considering the Ramsey-optimal policy rule and investigating optimal, simple, and implementable interest rate rules that augment domestic or external financial variables in an open-economy framework.

Glocker and Towbin (2012) investigate the interaction of alternative monetary policy rules and reserve requirements within a model of financial accelerator in which firms borrow either only from domestic depositors or foreign investors. Medina and Roldós (2014) focus on the effects of alternative parameterized monetary and macroprudential policy rules in an open economy with a modeling of the financial sector that is different from ours. They find that the LAW capabilities of conventional monetary policy might be limited. Akinci and Queralto (2014) consider occasionally binding leverage constraints faced by banks that can also issue new equity within a small open-economy model. They show that macroprudential taxes and subsidies are effective in lowering the probability of financial crises and that they increase welfare. However, they abstract from nominal rigidities and the role of monetary policy in relation to financial stability in EMEs. Kolasa and Lombardo (2014) study optimal monetary policy in a two-country DSGE model of the euro area with financial frictions as in Bernanke, Gertler, and Gilchrist (1999), and under which firms can collect both domestic and foreign-currency-denominated debt. They find that the monetary authority should correct credit market distortions at the expense of deviations from price stability.

In a closely related paper, Aoki, Benigno, and Kiyotaki (2016) consider monetary and financial policies in EMEs using a small open-economy New Keynesian setup with banks that are subject to currency risk. They model financial policies as net worth subsidies, which are financed by taxes on risky assets or foreign currency borrowing, and show that there are significant gains from combining such measures with monetary policy. Our paper generalizes their finding that from a welfare-maximizing point of view, interest rate policy displays a stronger anti-inflationary stance when it is either augmented with a financial stabilization objective or accompanied by an additional financial stabilization tool such as reserve requirements. This finding hinges on the property that, all else equal, a stronger anti-inflationary stance of an interest rate policy without any financial stabilization objective hurts bank balance sheets more, as it increases the cost of funds for banks, leading to a lower welfare. Our paper differs from the work of Aoki, Benigno, and Kiyotaki (2016) in three main ways. First, we model asymmetric financial frictions between domestic and foreign borrowing of banks differently. Second, and most importantly, our paper analyzes optimal Ramsey policy and optimized augmented interest rate rules rather than comparing parameterized alternative policy rules. Third, financial policies in our paper include LAW-type Taylor rules and reserve requirements instead of taxes on foreign debt or risky assets.

Under certain cases, optimal interest rate policy in our work calls for a positive response to exchange rate depreciations. This places our paper within the strand of literature surveyed by Engel (2014a) which makes a case for targeting currency mismatches in order to ease financial conditions faced by borrowers (in our case banks). Finally, our analysis also sheds light on the discussions regarding the monetary trilemma and the associated challenges that the EME monetary policymakers face as discussed by Obstfeld (2015) and Rey (2015).

This paper contributes to the literature surveyed above in four main respects. First, in a small open-economy setup, we investigate the optimality of responding to developments in domestic financial conditions as well as fluctuations in the exchange rate that are linked to capital flows which are highly relevant for EMEs. Second, we study the role of a banking sector which can raise both domestic and foreign funds in the transmission of augmented interest rate and reserve requirements policies. Third, we derive analytically the intratemporal and intertemporal wedges in the model economy, and characterize the optimal monetary policy rule by solving the Ramsey planner's problem. Finally, we construct optimal and simple augmented interest rate policy rules as well as an optimal policy mix of a conventional Taylor rule and a macroprudential reserve requirements policy.

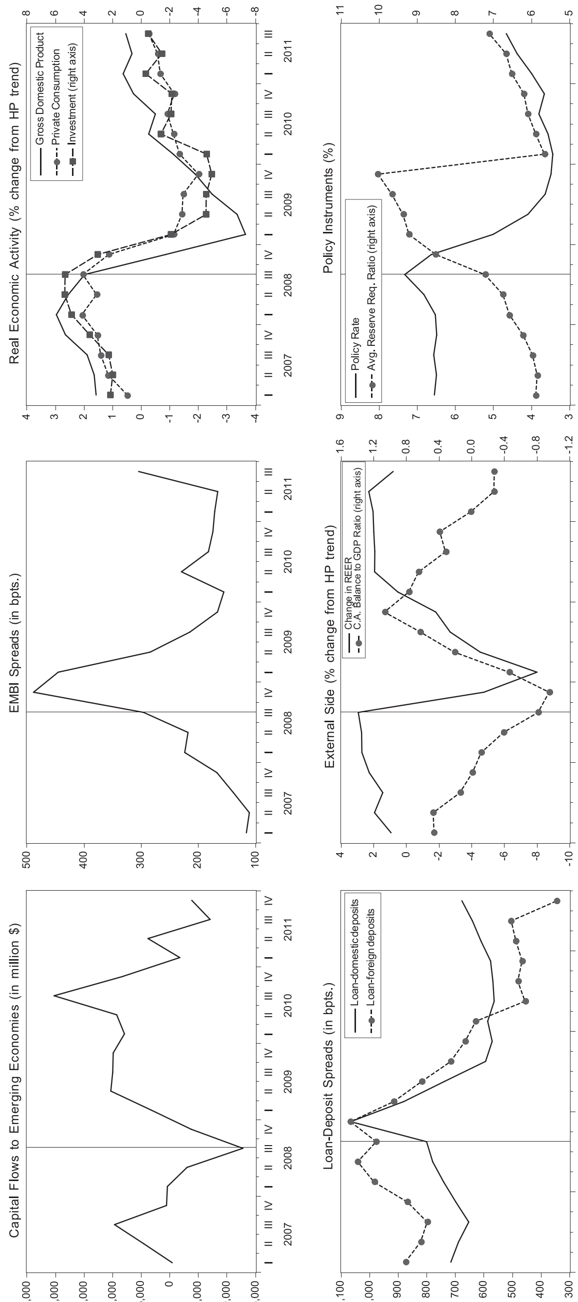
The rest of the paper is structured as follows. Section 2 provides a systematic documentation of the adverse feedback loop faced by EMEs during the global financial crisis. In section 3, we describe our theoretical framework. Section 4 focuses on our quantitative analysis and investigates optimal, simple, and implementable monetary policy rules for EMEs. Finally, section 5 concludes.

2. The 2007–09 Crisis and Macroeconomic Dynamics in the EMEs

Although the 2007–09 crisis originated in advanced economies, EMEs experienced the severe contractionary effects induced by it, as figure 1 clearly illustrates for twenty EMEs around the 2007–09 episode. In the figure, variables regarding the real economic activity and the external side are depicted by cross-country simple means of deviations from Hodrick-Prescott (HP) trends.[5] The top-left panel of the figure illustrates that the sharp reversal of capital inflows to EMEs is accompanied by an increase of roughly 400 basis points in the country borrowing premiums (the top-middle panel), as measured by the EMBI Global spread, leading to sharp hikes in lending spreads over the costs of domestic and foreign funds by around 400 basis points (the bottom-left panel). Finally, the cyclical components of the real effective exchange rate and current-account-to-GDP ratio (illustrated in the bottom-middle panel) displayed a depreciation and a reversal of about 10 percent and 2 percent,

[5] Data sources used in this section are the Bank for International Settlements, Bloomberg, EPFR, International Monetary Fund, and individual country central banks. Countries included in the analysis are Brazil, Chile, China, Colombia, Czech Republic, Hungary, India, Indonesia, Israel, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, Singapore, South Africa, Thailand, and Turkey. Using medians of deviations for the plotted variables produces similar patterns.

Figure 1. Macroeconomic Dynamics around the 2007–09 Crisis in Emerging Market Economies



respectively. In addition to these facts, Mihaljek (2010) documents that the tightening in domestic financial conditions in EMEs coincides with substantial declines in domestic deposits and disproportionately more reduction in foreign borrowing of banks, which resulted in dramatic falls in their loans to corporations. As a result of these adverse developments in domestic and external financial conditions, GDP and consumption declined by around 4 percent and investment fell by 8 percent compared with their HP trend levels in EMEs.

With the intention of mitigating the crisis, EME central banks first raised policy rates to curb accelerating capital outflows in the initial phase, and then gradually eased their policy stances (by about 4 percentage points in six quarters) thanks to the accommodative policies of advanced economies during the crisis (the bottom-right panel of figure 1). Reserve requirements, on the other hand, complemented conventional monetary policy at the onset of the crisis and appeared to replace it when there was a sharp upward reversal in capital flows in the aftermath of the crisis.[6]

We also illustrate cross-sectional developments in the EME group by providing table 1, which displays the peak-to-trough changes in macroeconomic and financial variables in the 2007:Q1–2011:Q3 episode for each individual EME in our sample. The average changes in variables might be different than those plotted in figure 1 since the exact timing of peak-to-trough is different for each EME. The table indicates that there is a substantial heterogeneity among EMEs in terms of the realized severity of the financial crisis.

All in all, it is plausible to argue that the 2007–09 global financial crisis exposed EMEs to an adverse feedback loop of capital outflows, depreciating exchange rates, deteriorating balance sheets, rising credit spreads, and falling real economic activity. The policy response of authorities in these countries, on the other hand, is strongly affected by the repercussions of the unconventional policy measures introduced by advanced economies and displayed diversity in the set of policy tools used. The next section provides a theory

[6]The abrupt decline of about 4 percentage points in reserve requirements from 2009:Q4 to 2010:Q1 is mostly due to Colombia and Peru, as they reduced their reserve requirement ratios by 16 and 9 percentage points, respectively.

Table 1. Macroeconomic Dynamics in 2007:Q1–2011:Q3 Episode (peak to trough)

Country	EMBI Spread (bps)	Output (%)	Consumption (%)	Investment (%)	CAD/ Output (pp)
Brazil	279	−7.6	−4.8	−23.0	1.43
Chile	260	−8.2	−15.0	−29.2	–
China	175	−3.6	–	–	2.70
Colombia	379	−6.5	−4.9	−17.3	1.53
Czech Rep.	–	−7.5	−6.3	−19.8	2.50
Hungary	477	−7.5	−10.2	−17.1	5.60
India	–	−1.8	−4.3	−11.3	1.53
Indonesia	597	−1.8	−7.7	−5.1	2.38
Israel	–	−4.1	−7.9	−20.4	8.70
Korea Rep.	–	−6.0	−7.8	−5.2	4.80
Malaysia	297	−10.2	−7.2	−17.7	3.20
Mexico	330	−9.8	−9.6	−14.0	1.87
Peru	392	−7.1	−8.0	−21.6	4.60
Philippines	391	−5.3	−5.7	−14.7	4.90
Poland	266	−3.8	−3.2	−19.3	2.80
Russia	703	−13.6	−10.6	−20.0	–
Singapore	162	−15.5	–	–	3.10
S. Africa	489	−5.2	−8.5	−26.1	6.30
Thailand	–	−10.6	−8.7	−27.0	7.40
Turkey	345	−19.7	−19.4	−41.0	4.90
Average	369	−7.7	−8.3	−19.4	3.90

Country	REER[a] (%)	Spread over Dom. (bps)	Spread over For. (bps)	Policy Rate (pp)	Res. Req. (pp)
Brazil	24.7	970	1000	−5.00	−3.33
Chile	20.0	700	1140	−7.80	0.00
China	12.3	900	1240	−1.89	−2.50
Colombia	21.9	830	1030	−7.00	−16.0
Czech Rep.	12.6	–	–	−3.00	0.00
Hungary	19.8	190	260	−4.70	−1.00
India	15.0	–	–	−4.20	−4.00
Indonesia	22.1	86	410	−2.75	–
Israel	8.3	–	–	−3.75	0.00
Korea Rep.	37.3	–	–	−3.25	–
Malaysia	7.5	41	188	−1.50	−3.00
Mexico	22.0	183	440	−3.75	0.00
Peru	8.1	120	330	−5.20	−9.00
Philippines	12.6	107	254	−3.50	−2.00
Poland	27.2	221	−225	−2.50	−0.50
Russia	16.3	380	460	−5.00	−3.00
Singapore	5.2	–	–	−2.43	0.00
S. Africa	29.0	−98	460	−6.50	–
Thailand	9.3	–	–	−3.25	0.00
Turkey	19.9	1480	340	−11.5	−1.50
Average	17.5	436	523	−4.4	−2.69

[a] An increase in the real effective exchange rate corresponds to a depreciation.

that replicates these features of the data and explores what kind of monetary policy design could be deemed as optimal from a welfare point of view.

3. Model Economy

The analytical framework is a medium-scale New Keynesian small open-economy model inhabited by households, non-financial firms, capital producers, and a government. There is a single tradable consumption good which is both produced at home and imported (exported) from (to) the rest of the world. Intermediate goods producers use capital and labor and determine the nominal price of their good in a monopolistically competitive market subject to menu costs as in Rotemberg (1982). Final goods producers, on the other hand, repackage the domestically produced and imported intermediate goods in a competitive market in which the prices of aggregated home and foreign goods are determined. Home goods are consumed by workers and capital goods producers, and are exported to the rest of the world. Similarly, foreign goods are consumed by workers and are used by capital goods producers.

Households are composed of worker and banker members who pool their consumption together. Workers earn wages and profit income; save in domestic-currency-denominated, risk-free bank deposits; and derive utility from consumption, leisure, and holding money balances. Different from standard open-economy models, we assume that workers do not trade international financial assets, since banker members of households carry out the balance of payments operations of this economy by borrowing from abroad.

Intermediate goods producers do not have access to household savings directly and instead finance their capital expenditures by selling equity claims to bankers. After financing their capital expenditures, they buy capital from capital producers who use home and foreign investment goods as inputs, repair the worn-out capital, and produce new capital.

Financial frictions define bankers as the key agents in the economy. The modeling of the banking sector follows Gertler and Kiyotaki (2011), with the modification that bankers make external financing from both domestic depositors and international investors, potentially bearing currency risk. With their debt and equity, bankers fund their assets that come in the form of firm securities. Finally, the consolidated government makes an exogenous stream of spending and determines short-term interest rate as well as reserve requirements policy.

The benchmark monetary policy regime is a Taylor rule that aims to stabilize inflation and output. In order to understand the effectiveness of alternative monetary policy rules, we augment the baseline policy framework with a number of various domestic or external financial stability objectives. In addition, we analyze the use of reserve requirements that countercyclically respond to credit spreads over the cost of non-core bank borrowing. Unless otherwise stated, variables denoted by uppercase (lowercase) letters represent nominal (real) values in domestic currency. Variables that are denominated in foreign currency or related to the rest of the world are indicated by an asterisk. For brevity, we include only key model equations in the main text. Interested readers might refer to online appendix A (available at http://www.ijcb.org) for detailed descriptions of the optimization problems of workers, firms, capital producers, and bankers as well as the definition of the competitive equilibrium.

3.1 Prices

The nominal exchange rate of the foreign currency in domestic currency units is denoted by S_t. Therefore, the real exchange rate of the foreign currency in terms of real home goods becomes $s_t = \frac{S_t P_t^*}{P_t}$, where foreign-currency-denominated CPI, P_t^*, is taken exogenously. We assume that foreign goods are produced in a symmetric setup as in home goods. That is, there is a continuum of foreign intermediate goods that are bundled into a composite foreign good, whose consumption by the home country is denoted by c_t^F. We assume that the law of one price holds for the import prices of intermediate goods, that is, $MC_t^F = S_t P_t^{F*}$, where MC_t^F is the marginal cost for intermediate good importers and P_t^{F*} is the foreign-currency-denominated price of such goods. Foreign intermediate goods producers charge a markup over the marginal cost MC_t^F while setting the domestic-currency-denominated price of foreign goods. The small open economy also takes P_t^{F*} as given. In online appendix A.5, we elaborate further on the determination of the domestic-currency-denominated prices of home and foreign goods, P_t^H and P_t^F.

3.2 Banks

The modeling of banks closely follows Gertler and Kiyotaki (2011) except that banks in our model borrow in local currency from domestic households and in foreign currency from international lenders. They combine these funds with their net worth, and finance capital expenditures of home-based tradable goods producers. For tractability, we assume that banks only lend to home-based production units.

The main financial friction in this economy originates from a moral hazard problem between bankers and their funders, leading to an endogenous borrowing constraint on the former. The agency problem is such that depositors (both domestic and foreign) believe that bankers might divert a certain fraction of their assets for their own benefit. Additionally, we formulate the diversion assumption in a particular way to ensure that, in equilibrium, an endogenous positive spread between the costs of domestic and foreign borrowing emerges, as in the data. Ultimately, in equilibrium, the diversion friction restrains funds raised by bankers and limits the credit extended to non-financial firms, leading up to non-negative credit spreads.

Banks are also subject to symmetric reserve requirements on domestic and foreign deposits, i.e., they are obliged to hold a certain fraction of domestic and foreign deposits rr_t, within the central bank. We retain this assumption to facilitate the investigation of reserve requirements as an additional policy tool used by the monetary authority.

3.2.1 Balance Sheet

The period-t balance sheet of a banker j denominated in domestic currency units is

$$Q_t l_{jt} = B_{jt+1}(1 - rr_t) + S_t B^*_{jt+1}(1 - rr_t) + N_{jt}, \qquad (1)$$

where B_{jt+1} and B^*_{jt+1} denote domestic deposits and foreign debt (in nominal foreign currency units), respectively. N_{jt} denotes the banker's net worth, Q_{jt} is the nominal price of securities issued by non-financial firms against their physical capital demand, and l_{jt} is the quantity of such claims. rr_t is the required reserves ratio on domestic and foreign deposits. It is useful to divide equation (1) by the aggregate price index P_t and rearrange terms to obtain banker j's balance sheet in real terms. Those manipulations imply

$$q_t l_{jt} = b_{jt+1}(1 - rr_t) + b^*_{jt+1}(1 - rr_t) + n_{jt}, \tag{2}$$

where q_t is the relative price of the security claims purchased by bankers and $b^*_{jt+1} = \frac{S_t B^*_{jt+1}}{P_t}$ is the foreign borrowing in real domestic currency units. Notice that if the exogenous foreign price index P^*_t is assumed to be equal to 1 at all times, then b^*_{jt+1} incorporates the impact of the real exchange rate, $s_t = \frac{S_t}{P_t}$, on the balance sheet.

Next period's real net worth, n_{jt+1}, is determined by the difference between the return earned on assets (loans and reserves) and the cost of debt. Therefore we have

$$n_{jt+1} = R_{kt+1} q_t l_{jt} + rr_t(b_{jt+1} + b^*_{jt+1}) - R_{t+1} b_{jt+1} - R^*_{t+1} b^*_{jt+1}, \tag{3}$$

where R_{kt+1} denotes the state-contingent gross real return earned on the purchased claims issued by the production firms. R_{t+1} is the gross real risk-free deposit rate offered to domestic workers, and R^*_{t+1} is the gross country borrowing rate of foreign debt, denominated in real domestic currency units. The gross real interest rates, R_{t+1} and R^*_{t+1}, are defined as follows:

$$\begin{aligned} R_{t+1} &= (1 + r_{nt}) \frac{P_t}{P_{t+1}} \\ R^*_{t+1} &= \Psi_t (1 + r^*_{nt}) \frac{S_{t+1}}{S_t} \frac{P_t}{P_{t+1}} \quad \forall t, \end{aligned} \tag{4}$$

where r_n denotes the net nominal deposit rate, which is equal to the policy rate set by the central bank, and r^*_n denotes the net nominal international borrowing rate. Bankers face a premium over this rate while borrowing from abroad. Specifically, the premium is an increasing function of foreign debt, that is, $\Psi_t = \exp\left(\psi_1 \hat{b^*_{t+1}}\right) \psi_t$, where $\hat{b^*_{t+1}}$ represents the log-deviation of the aggregate foreign debt of bankers from its steady-state level, $\psi_1 > 0$ is the foreign debt elasticity of country risk premium, and ψ_t is a random disturbance to this premium.[7] Particularly, we assume ψ_t follows,

$$\log(\psi_{t+1}) = \rho^{\psi} \log(\psi_t) + \epsilon_{t+1}^{\psi},$$

with zero mean and constant variance Gaussian innovations ϵ_{t+1}^{Ψ}. Introducing ψ_t enables us to study the domestic business cycle responses to exogenous cycles in capital flows. In order to capture the impact of the U.S. monetary policy normalization on emerging economies, we assume that exogenous world interest rates follow an autoregressive process denoted by

$$r_{nt+1}^{*} = \rho^{r_n^*} r_{nt}^{*} + \epsilon_{t+1}^{r_n^*}.$$

The innovations $\epsilon_{t+1}^{r_n^*}$ are normally distributed with zero mean and constant variance $\sigma^{r_n^*}$. Solving for b_{jt+1} in equation (2), substituting in equation (3), and rearranging terms imply that bank's net worth evolves as

$$n_{jt+1} = \left[R_{kt+1} - \hat{R}_{t+1}\right] q_t l_{jt} + \left[R_{t+1} - R_{t+1}^{*}\right] b_{jt+1}^{*} + \hat{R}_{t+1} n_{jt}, \tag{5}$$

with $\hat{R}_{t+1} = \frac{R_{t+1} - rr_t}{1 - rr_t}$ representing the required reserves adjusted domestic deposit rate. This equation illustrates that individual bankers' net worth depends positively on the premium of the return earned on assets over the reserves adjusted cost of borrowing, $R_{kt+1} - \hat{R}_{t+1}$. The second term on the right-hand side shows the benefit of raising foreign debt as opposed to domestic debt, as foreign debt is cheaper in expected terms due to asymmetric financial frictions. Finally, the last term highlights the contribution of internal funds, which are multiplied by $\hat{R}_{t+1}$, the opportunity cost of raising one unit of external funds via domestic borrowing.

Banks would find it profitable to purchase securities issued by non-financial firms only if

$$E_t \left\{ \Lambda_{t,t+i+1} \left[R_{kt+i+1} - \hat{R}_{t+i+1}\right] \right\} \geq 0 \quad \forall t,$$

[7] By assuming that the cost of borrowing from international capital markets increases in the net foreign indebtedness of the aggregate economy, we ensure the stationarity of the foreign asset dynamics as in Schmitt-Grohé and Uribe (2003).

where $\Lambda_{t,t+i+1} = \beta^{i+1}\left[\frac{U_c(t+i+1)}{U_c(t)}\right]$ denotes the $i+1$-periods-ahead stochastic discount factor of households, whose banker members operate as financial intermediaries. Notice that in the absence of financial frictions, an abundance of intermediated funds would cause R_k to decline until this premium is completely eliminated. In the following, we also establish that

$$E_t\left\{\Lambda_{t,t+i+1}\left[R_{t+i+1} - R^*_{t+i+1}\right]\right\} > 0 \ \ \forall t,$$

so that the cost of domestic debt entails a positive premium over the cost of foreign debt at all times.

In order to rule out any possibility of complete self-financing of bankers, we assume that bankers have a finite life and survive to the next period only with probability $0 < \theta < 1$. At the end of each period, $1-\theta$ measure of new bankers are born and are remitted $\frac{\epsilon^b}{1-\theta}$ fraction of the assets owned by exiting bankers in the form of startup funds.

3.2.2 Net Worth Maximization

Bankers maximize expected discounted value of the terminal net worth of their financial firm V_{jt} by choosing the amount of security claims purchased l_{jt} and the amount of foreign debt b^*_{jt+1}. For a given level of net worth, the optimal amount of domestic deposits can be solved for by using the balance sheet. Bankers solve the following value maximization problem:

$$V_{jt} = \max_{l_{jt+i}, b^*_{jt+1+i}} E_t \sum_{i=0}^{\infty} (1-\theta)\theta^i \Lambda_{t,t+1+i}\ n_{jt+1+i},$$

which can be written in recursive form as

$$V_{jt} = \max_{l_{jt}, b^*_{jt+1}} E_t\Big\{\Lambda_{t,t+1}[(1-\theta)n_{jt+1} + \theta V_{jt+1}]\Big\}. \tag{6}$$

For a non-negative premium on credit, the solution to the value maximization problem of banks would lead to an unbounded magnitude of assets. In order to rule out such a scenario, we follow Gertler and Kiyotaki (2011) and introduce an agency problem between depositors and bankers. Specifically, lenders believe that banks might renege on their liabilities and divert λ fraction of their total divertable assets, where such assets constitute total loans minus a fraction ω_l of domestic deposits. When lenders become aware of the potential confiscation of assets, they would initiate a bank run and lead to the liquidation of the bank altogether. In order to rule out bank runs in equilibrium, in any state of nature, bankers' optimal choice of l_{jt} should be incentive compatible. Therefore, the following constraint is imposed on bankers:

$$V_{jt} \geq \lambda\Big(q_t l_{jt} - \omega_l b_{jt+1}\Big), \tag{7}$$

where λ and ω_l are constants between zero and one. This inequality suggests that the liquidation cost of bankers from diverting funds V_{jt} should be greater than or equal to the diverted portion of assets. In equilibrium, bankers never divert (and default on) funds and accordingly adjust their demand for external finance to meet the incentive compatibility constraint in each period.

We introduce asymmetry in financial frictions by excluding ω_l fraction of domestic deposits from diverted assets. This is due to the idea that domestic depositors would arguably have a comparative advantage over foreign depositors in recovering assets in case of a bankruptcy. Furthermore, they would also be better equipped than international lenders in monitoring domestic bankers (see section 4.3 for further details.)

Our methodological approach is to approximate the stochastic equilibrium around the deterministic steady state. Therefore, we are interested in cases in which the incentive constraint of banks is always binding, which implies that (7) holds with equality. This is the case in which the loss of bankers in the event of liquidation is just equal to the amount of assets that they can divert.

We conjecture the optimal value of financial intermediaries to be a linear function of bank loans, foreign debt, and bank capital, that is,

$$V_{jt} = \nu_t^l q_t l_{jt} + \nu_t^* b_{jt+1}^* + \nu_t n_{jt}. \tag{8}$$

Among these recursive objects ν_t^l represents the expected discounted excess value of assets, ν_t^* stands for the expected discounted excess value of borrowing from abroad, and ν_t denotes the expected discounted marginal value of bank capital at the end of period t. The solution to the net worth maximization problem implies

$$q_t l_{jt} - \omega_l b_{jt+1} = \frac{\nu_t - \frac{\nu_t^*}{1-rr_t}}{\lambda - \zeta_t} n_{jt} = \kappa_{jt} n_{jt}, \tag{9}$$

where $\zeta_t = \nu_t^l + \frac{\nu_t^*}{1-rr_t}$. This endogenous constraint, which emerges from the costly enforcement problem described above, ensures that banks' leverage of risky assets is always equal to κ_{jt} and is decreasing with the fraction of divertable funds λ.

Replacing the left-hand side of (8) to verify our linear conjecture on bankers' value and using equation (5), we find that ν_t^l, ν_t, and ν_t^* should consecutively satisfy

$$\nu_t^l = E_t\Big\{\Xi_{t,t+1}\left[R_{kt+1} - \hat{R}_{t+1}\right]\Big\}, \tag{10}$$

$$\nu_t = E_t\Big\{\Xi_{t,t+1}\hat{R}_{t+1}\Big\}, \tag{11}$$

$$\nu_t^* = E_t\Big\{\Xi_{t,t+1}\left[R_{t+1} - R_{t+1}^*\right]\Big\}, \tag{12}$$

with $\Xi_{t,t+1} = \Lambda_{t,t+1}\left[1 - \theta + \theta\left(\zeta_{t+1}\kappa_{t+1} + \nu_{t+1} - \frac{\nu_{t+1}^*}{1-rr_{t+1}}\right)\right]$ representing the augmented stochastic discount factor of bankers, which is a weighted average defined over the likelihood of survival.

Equation (10) suggests that bankers' marginal valuation of total assets is the premium between the expected discounted total return to loans and the benchmark cost of domestic funds. Equation (11) shows that marginal value of net worth should be equal to the expected discounted opportunity cost of domestic funds, and lastly, equation (12) demonstrates that the excess value of raising foreign debt is equal to the expected discounted value of the premium in the cost of raising domestic debt over the cost of raising foreign debt. One can show that this spread is indeed positive, that is, $\nu_t^* > 0$, by studying first-order condition (A13) in online appendix A.2 and observing that $\lambda, \mu, \omega_l > 0$ and $rr_t < 1$, with μ denoting the Lagrange multiplier of bankers' problem.

The definition of the augmented pricing kernel of bankers is useful in understanding why banks shall be a veil absent financial frictions. Specifically, the augmented discount factor of bankers can be rewritten as $\Xi_{t,t+1} = \Lambda_{t,t+1}\left[1 - \theta + \theta\lambda\kappa_{t+1}\right]$ by using the leverage constraint. Financial frictions would vanish when none of the assets are diverted—i.e., $\lambda = 0$—and bankers never have to exit—i.e., $\theta = 0$. Consequently, $\Xi_{t,t+1}$ simply collapses to the pricing kernel of households $\Lambda_{t,t+1}$. This case would also imply efficient intermediation of funds driving the arbitrage between the lending and deposit rates down to zero. The uncovered interest parity, on the other hand, is directly affected by the asymmetry in financial frictions. That is, as implied by equation (12), the uncovered interest parity obtains only when $\nu_t^* = 0$.

3.2.3 Aggregation

We confine our interest to equilibriums in which all households behave symmetrically, so that we can aggregate equation (9) over j and obtain the following aggregate relationship:

$$q_t l_t - \omega_l b_{t+1} = \kappa_t n_t, \tag{13}$$

where $q_t l_t$, b_{t+1}, and n_t represent aggregate levels of bank assets, domestic deposits, and net worth, respectively. Equation (13) shows that the aggregate credit net of non-divertable domestic deposits can only be up to an endogenous multiple of the aggregate bank capital. Furthermore, fluctuations in asset prices, q_t, would feed back into fluctuations in bank capital via this relationship. This would be the source of the financial accelerator mechanism in our model.

The evolution of the aggregate net worth depends on that of the surviving bankers n_{et+1}, which might be obtained by substituting the aggregate bank capital constraint (13) into the net worth evolution equation (5) and adding up the startup funds of the new entrants n_{nt+1}. The latter is equal to $\frac{\epsilon^b}{1-\theta}$ fraction of exiting banks' assets $(1-\theta)q_t l_t$. Therefore, $n_{nt+1} = \epsilon^b q_t l_t$. As a result, the transition for the aggregate bank capital becomes $n_{t+1} = n_{et+1} + n_{nt+1}$.

3.3 Monetary Authority and the Government

The monetary authority sets the short-term nominal interest rate via a simple (and implementable) monetary policy rule that includes only a few observable macroeconomic variables and ensures a unique rational expectations equilibrium.[8] We consider Taylor-type interest rate rules that respond to deviations of an augmenting variable f_t in addition to inflation and output from their steady-state levels,

$$\log\left(\frac{1+r_{nt}}{1+\overline{r_n}}\right) = \rho_{r_n}\log\left(\frac{1+r_{nt-1}}{1+\overline{r_n}}\right) + (1-\rho_{r_n})\left[\varphi_\pi \log\left(\frac{1+\pi_t}{1+\overline{\pi}}\right)\right.$$
$$\left. + \varphi_y \log\left(\frac{y_t^H}{\overline{y^H}}\right) + \varphi_f \log\left(\frac{f_t}{\overline{f}}\right)\right], \tag{14}$$

where r_{nt} is the short-term policy rate, π_t is the net CPI inflation rate, y_t^H is home output, variables with bars denote respective steady-state values that are targeted by the central bank, and f_t corresponds to the level of bank credit, asset prices, real exchange rate, credit spreads, or the U.S. interest rate in alternative specifications. In each specification, φ_f measures the responsiveness of the interest rate rule to the augmenting variable of interest. To be general, we allow for persistence in the monetary policy rule so that $0 \leq |\rho_{r_n}| < 1$.

In the benchmark specification, we assume that the required reserves ratio is fixed at $rr_t = \overline{rr}\ \forall t$, with $\overline{rr}$ denoting a steady-state level. In section 4.8 we investigate whether reserve requirements can be used in combination with conventional monetary policy to reduce the procyclicality of the financial system. In particular, we assume that required reserves ratios for both domestic and foreign deposits respond to deviations of the loan–foreign deposits spread from its steady-state value. That is,

$$\log\left(\frac{1+rr_t}{1+\overline{rr}}\right) = \rho_{rr}\log\left(\frac{1+rr_{t-1}}{1+\overline{rr}}\right)$$
$$+ (1-\rho_{rr})\left[\varphi_{rr}\log\left(\frac{R_{kt+1}-R^*_{t+1}}{\overline{R_k - R^*}}\right)\right], \tag{15}$$

with $0 < |\rho_{rr}| < 1$ and φ_{rr} is a finite real number. Notice that credit spreads are countercyclical, since the magnitude of intermediated funds declines in response to adverse shocks. Therefore, one might

[8]For further discussion on simple and implementable rules, see Schmitt-Grohé and Uribe (2007).

conjecture that the reserve requirement rule would support the balance sheet of bankers in bad times by reducing the effective tax on domestic and foreign liabilities as in Glocker and Towbin (2012) and Mimir, Taşkın, and Sunel (2013), implying a negative value for the optimized response coefficient φ_{rr}.

Money supply in this economy is demand determined and compensates for the cash demand of workers and the required reserves demand of bankers. Consequently, the money market clearing condition is given by

$$M_{0t} = M_t + rr_t B_{t+1},$$

where M_{0t} denotes the supply of monetary base in period t. As discussed by Schmitt-Grohé and Uribe (2007), the inclusion of cash balances would not alter the optimality of interest rate policy rules.

Government consumes a time-varying fraction of home goods g_t^H that follows the exogenous process

$$\ln(g_{t+1}^H) = (1 - \rho^{g^H}) \ln \bar{g^H} + \rho^{g^H} \ln(g_t^H) + \epsilon_{t+1}^{g^H},$$

where $\epsilon_{t+1}^{g^H}$ is a Gaussian process with zero mean and constant variance. We introduce this shock to capture disturbances in domestic aggregate demand.

The fiscal and monetary policy arrangements lead to the consolidated government budget constraint,

$$p_t^H g_t^H y_t^H = \frac{M_t - M_{t-1}}{P_t} + \frac{rr_t B_{t+1} - rr_{t-1} B_t}{P_t} + \frac{T_t}{P_t}.$$

Lump-sum taxes $\tau_t = \frac{T_t}{P_t}$ are determined endogenously to satisfy the consolidated government budget constraint at any date t. The resource constraints and the definition of competitive equilibrium are included in online appendix A.

4. Quantitative Analysis

This section analyzes quantitative predictions of the model by studying the results of numerical simulations of an economy calibrated to a typical emerging market, Turkey, for which financial frictions in the banking sector and monetary policy tools analyzed here are particularly relevant. To investigate the dynamics of the model and carry out welfare calculations, we compute a second-order approximation to the equilibrium conditions. All computations are conducted using the open-source package Dynare.

4.1 Model Parameterization and Calibration

Table 2 lists the parameter values used for the quantitative analysis of the model economy. The reference period for the long-run ratios implied by the Turkish data is 2002–14. The data sources for empirical targets are the Central Bank of the Republic of Turkey (CBRT, hereafter) and the Banking Regulation and Supervision Agency. The preference and production parameters are set to values that are standard in the business cycle literature. Starting with the former, we set the quarterly discount factor $\beta = 0.9821$ to match the average annualized real deposit rate of 7.48 percent observed in Turkey over the sample period. The relative risk aversion $\sigma = 2$ is taken from the literature. We calibrate the relative utility weight of labor $\chi = 199.348$ in order to fix hours worked in the steady state at 0.3333. The Frisch elasticity of labor supply parameter $\xi = 3$ and the habit persistence parameter $h_c = 0.7$ are set to values commonly used in the literature. The relative utility weight of money $\upsilon = 0.0634$ is chosen to match 2.25 as the quarterly output velocity of M2. Following the discussion in Faia and Monacelli (2007), we set the intratemporal elasticity of substitution for the consumption composite $\gamma = 0.5$. The intratemporal elasticity of substitution for the investment composite good $\gamma_i = 0.25$ is chosen as in Gertler, Gilchrist, and Natalucci (2007). The share of domestic goods in the consumption composite $\omega = 0.62$ is set to match the long-run mean of the domestic consumption share of output of 0.57.

We calibrate the financial-sector parameters to match some long-run means of financial variables for the 2002–14 period. Specifically, the fraction of assets that can be diverted $\lambda = 0.65$, the proportional transfer to newly entering bankers $\epsilon^b = 0.00195$, and the fraction of domestic deposits that cannot be diverted $\omega_l = 0.81$ are jointly calibrated to match the following three targets: an average domestic credit spread of 34 basis points, which is the difference between the quarterly commercial loan rate and the domestic deposit rate; an average bank leverage of 7.94; and the share of foreign funds in total

Table 2. Model Parameters

Description	Parameter	Value	Target
Preferences			
Quarterly Discount Factor	β	0.9821	Annualized real deposit rate of 7.48%
Relative Risk Aversion	σ	2	Literature
Scaling Parameter for Labor	χ	199.35	Steady-state hours worked of 0.33
Labor Supply Elasticity	ξ	3	Literature
Habit Persistence	h_c	0.7	Literature
Scaling Parameter for Money	υ	0.0634	$Y/M2 = 2.25$
Elasticity of Substitution for Consumption Composite	γ	0.5	Faia and Monacelli (2007)
Elasticity of Substitution for Investment Composite	γ_i	0.25	Gertler, Gilchrist, and Natalucci (2007)
Share of Domestic Goods in the Consumption Composite	ω	0.62	$C^H/Y^H = 0.57$
Financial Intermediaries			
Fraction of Diverted Bank Loans	λ	0.65	Domestic credit spread = 34 bps.
Proportional Transfer to the Entering Bankers	ϵ^b	0.00195	Commercial bank leverage = 7.94
Fraction of Non-diverted Domestic Deposits	ω_l	0.81	Banks' foreign debt share = 40.83%
Survival Probability of Bankers	θ	0.925	Survival duration of 3.33 years for bankers
Firms			
Share of Capital in Output	α	0.4	Labor share of output = 0.60
Share of Domestic Goods in the Investment Composite	ω_i	0.87	$I^H/Y^H = 0.15$
Steady-State Utilization Rate	$\bar{u}$	1	Literature
Depreciation Rate of Capital	δ	0.035	$I/K = 14.8\%$
Utilization Elasticity of Marginal Depreciation Rate	ϱ	1	Gertler, Gilchrist, and Natalucci (2007)
Investment Adjustment Cost Parameter	ψ	5	Elasticity of price of capital w.r.t. I/K ratio = 0.125
Elasticity of Substitution between Varieties	ϵ	11	Steady-state markup of 1.1
Menu Cost Parameter for Domestic Intermediate Goods	φ_H	113.88	Price inertia likelihood = 0.75
Menu Cost Parameter for Foreign Intermediate Goods	φ_F	113.88	Price inertia likelihood = 0.75
Foreign Price Elasticity of Export Demand	Γ	1	Literature
Share of Foreign Output in Export Demand	υ^F	0.25	Gertler, Gilchrist, and Natalucci (2007)
Average Foreign Output	$\bar{y*}$	0.16	$X/Y = 0.18$

(*continued*)

Table 2. (Continued)

Description	Parameter	Value	Target
Monetary Authority and Government			
Policy Rate Persistence	ρ_{r_n}	0.89	Estimated for 2003:Q1–2014:Q4
Policy Rate Inflation Response	φ_π	2.17	Estimated for 2003:Q1–2014:Q4
Required Reserves Ratio	rr	0.09	Average required reserves ratio for 1996–2015
Steady-State Government Expenditure to GDP Ratio	$\bar{g}^H$	0.10	$G/Y = 10\%$
Shock Processes			
Persistence of Government Spending Shocks	ρ^{gH}	0.457	Estimated for 2002–14
Standard Deviation of Government Spending Shocks	σ^{gH}	0.04	Estimated for 2002–14
Persistence of Risk Premium Shocks	ρ^Ψ	0.963	Estimated from EMBI Global for 1996:Q2–2014:Q4
Standard Deviation of Risk Premium Shocks	σ^Ψ	0.0032	Estimated from EMBI Global for 1996:Q2–2014:Q4
Foreign Debt Elasticity of Risk Premium	ψ_1	0.015	$corr(TB/Y, Y) = -0.76$
Persistence of U.S. Interest Rate Shocks	ρ_n^{R*}	0.977	Estimated for 1996:Q2–2014:Q4
Standard Deviation of U.S. Interest Rate Shocks	σ_n^{R*}	0.00097	Estimated for 1996:Q2–2014:Q4
Persistence of TFP Shocks	ρ^A	0.662	Bahadir and Gumus (2014)
Standard Deviation of TFP Shocks	σ^A	0.0283	Bahadir and Gumus (2014)
Persistence of Export Demand Shocks	ρ^{y*}	0.425	Persistence of the EU GDP = 0.31
Standard Deviation of Export Demand Shocks	σ^{y*}	0.0048	Standard deviation of the EU GDP = 0.0048

bank liabilities, which is around 40 percent for commercial banks in Turkey. We also pick the survival probability of bankers θ as 0.925, which implies an average survival duration of nearly three-and-a-half years for bankers.

Regarding the technology parameters, the share of capital in the production function $\alpha = 0.4$ is set to match the share of labor income in Turkey. We pick the share of domestic goods in the investment composite $\omega_i = 0.87$ to match the long-run mean of the domestic investment share of output of 15 percent. The steady-state utilization rate is normalized at one and the quarterly depreciation rate of capital $\delta = 3.5\%$ is chosen to match the average annual investment-to-capital ratio. The elasticity of marginal depreciation with respect to the utilization rate $\varrho = 1$ is set as in Gertler, Gilchrist, and Natalucci (2007). The investment adjustment cost parameter is calibrated to $\psi = 5$, which implies a long-run elasticity of the price of capital with respect to the investment-to-capital ratio of 0.125, which is in line with the literature. We set the elasticity of substitution between varieties in final output $\epsilon = 11$ to have a steady-state markup value of 1.1. Rotemberg price adjustment cost parameters in domestic and foreign intermediate goods production $\varphi_H = \varphi_F = 113.88$ are chosen to imply a probability of 0.75 of not changing prices in both sectors. We pick the elasticity of export demand with respect to foreign prices $\Gamma = 1$ and the foreign output share parameter $\nu^F = 0.25$ as in Gertler, Gilchrist, and Natalucci (2007). Given these parameters, the mean of foreign output $\bar{y^*} = 0.16$ is chosen to match the long-run mean of the exports-to-output ratio of 18 percent.

We estimate a standard Taylor rule for the Turkish economy to approximate the monetary policy implemented in Turkey. In the estimation, we use the CBRT's average funding rate, which is the effective policy rate, over the period 2003–14. The resulting estimated interest rate rule persistence is $\rho_{r_n} = 0.89$ and the inflation rate response is $\varphi_\pi = 2.17$. The estimated response coefficient of output turned out not to be statistically different from zero. We then use these estimated parameters to calibrate the standard Taylor-rule parameters in the model of the decentralized economy. Moreover, the long-run value of required reserves ratio $\bar{rr} = 0.09$ is set to its time-series average level for the period 1996–2015. The steady-state government-expenditures-to-output ratio $\bar{g^H} = 10\%$

reflects the value implied by the Turkish data for the 2002–14 period.

Finally, we estimate three independent AR(1) processes for the share of public demand for home goods g_t^H, country risk premium Ψ_{t+1}, and the U.S. interest rate R^*_{nt+1}, where $\epsilon^{g^H}_{t+1}$, ϵ^{Ψ}_{t+1}, and $\epsilon^{R^*_n}_{t+1}$ are iid Gaussian shocks. We use J.P. Morgan's EMBI Global Turkey data in the estimation of country risk premium shocks. The resulting estimated persistence parameters are $\rho^{g^H} = 0.457$, $\rho^{\Psi} = 0.963$, and $\rho^{R^*_n} = 0.977$. The estimated standard deviations are $\sigma^{g^H} = 0.04$, $\sigma^{\Psi} = 0.0032$, and $\sigma^{R^*_n} = 0.001$. The long-run mean of quarterly foreign interest rate is set to 64 basis points to match quarterly interest rate in the United States for the period 1996–2014, and the long-run foreign inflation rate is set to zero. The foreign debt elasticity of risk premium is set to $\psi_1 = 0.015$. Parameters underlying the total factor productivity (TFP) shock are taken from Bahadir and Gumus (2014), who estimate an AR(1) process for the Solow residuals coming from tradable output in Turkey for the 1999:Q1–2010:Q1 period. Their estimates for the persistence and volatility of the tradable TFP emerge as $\rho^A = 0.662$ and $\sigma^A = 0.0283$. Finally, we calibrate the export demand shock process under all shocks to match both the persistence and the volatility of GDP of the European Union, which are 0.31 and 0.48 percent, respectively.[9] The implied persistence and volatility parameters are $\rho^{y^*} = 0.977$ and $\sigma^{y^*} = 0.0048$.

4.2 Model versus Data

The quantitative performance of the decentralized model economy operating under the standard Taylor rule calibrated to the Turkish data is illustrated in table 3, in which the relative volatilities, correlations with output, and autocorrelations of the simulated time series are compared with corresponding moments implied by the data. The first column of the table shows that for the reference time

[9] We use the GDP of the European Union (EU) for the calibration of export demand shocks because it is the main trading partner of Turkey with the largest share in the data over the past decade. The average share of the EU in Turkey's exports is 46 percent over the period from 2007 to 2016. The trade data are taken from the Turkish Statistical Agency (http://www.tuik.gov.tr).

Table 3. Business Cycle Statistics: Data vs. Model Economy

Variable	$\frac{\partial_x}{\partial_y}$ Data	D.E.[a]	$corr(x, y)$ Data	D.E.	$corr(x_t, x_{t-1})$ Data	D.E.
Real Variables						
Output	1.00	1.00	1.00	1.00	0.84	0.83
Consumption	0.76	0.70	0.92	0.86	0.72	0.93
Investment	2.58	4.93	0.96	0.83	0.87	0.95
Financial Variables						
Liability Composition (Foreign)	1.16	1.95	−0.03	−0.20	0.53	0.95
Credit	1.78	2.25	0.54	0.72	0.69	0.79
Loan–Domestic Deposit Spread	0.23	0.20	−0.55	−0.65	0.65	0.83
Loan–Foreign Deposit Spread	0.81	0.37	−0.37	−0.48	0.55	0.74
External Variables						
Real Exchange Rate	1.20	5.95	−0.26	−0.34	0.50	0.66
CA Balance to GDP	0.38	1.05	−0.67	−0.50	0.90	0.71
Trade Balance to GDP	0.46	0.33	−0.79	−0.76	0.72	0.94
Monetary Variables						
Inflation Rate	0.16	0.34	−0.32	−0.18	0.73	0.50
Policy Rate	0.18	0.11	−0.17	−0.83	0.78	0.89

[a]D.E. denotes the decentralized economy.

period, consumption is less volatile than output, whereas investment is more volatile in the data. When financial variables are considered, we observe that credit spreads are less volatile than output, whereas bankers' foreign debt share and loans are more volatile. The data also suggest that the real exchange rate is more volatile than output, while the current-account-to-output and trade-balance-to-output ratios are less volatile. Finally, inflation and policy rates are less volatile than output in the data. The second column of table 3 reports that despite the fact that the benchmark model is not estimated and includes a few number of structural shocks, it is able to generate the relative volatilities of model variables of interest that are mostly in line with the data.

When the correlations with output and autocorrelations are considered, the benchmark model performs well on quantitative grounds as well. Columns 3 and 4 imply that the model is able to generate same signs for correlations of all model variables in interest with output. Most importantly, credit spreads, the real exchange rate, the ratio of current account balance to GDP, and inflation are countercyclical, whereas bank credit, investment, and consumption are procyclical. Furthermore, apart from the short-term interest rate, the level of model-implied correlation coefficients are fairly similar to those implied by the data. These patterns are also observed for the model-generated autocorrelations in comparison with the data, as shown in the last two columns of the table.

Table 4 reports asymptotic variance decomposition of main model variables under domestic and external shocks operating simultaneously. The unconditional variance decomposition results illustrate that country risk premium and world interest rate shocks explain most of the variation in financial and external variables as well as a considerable part of the variation in the inflation and the short-term interest rates. Remarkably, the U.S. interest rate shocks in isolation explain about 12 percent of the variation in model variables on average, whereas the explanatory power of country premium shocks is much stronger, which is fairly different than what the findings of Uribe and Yue (2006) suggest. TFP shocks, on the other hand, roughly account for one-third of volatilities in output, credit, and the inflation rate, and one-quarter of the variation in policy rates. Export demand and government spending shocks drive a negligible part of fluctuations in model variables, with the only

Table 4. Asymptotic Variance Decomposition in the Decentralized Economy (%)

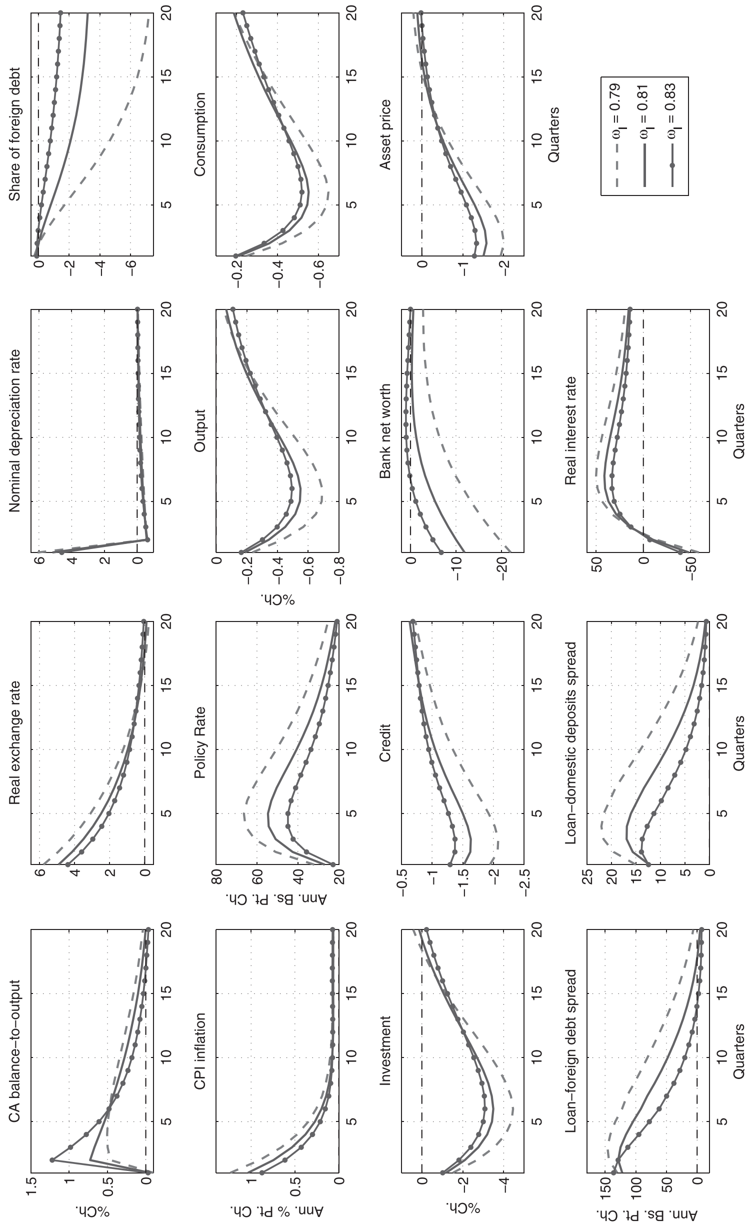
Variables	TFP	Government Spending	Country Risk Premium	U.S. Interest Rate	Export Demand
Output	32.66	16.38	43.39	7.39	0.18
Consumption	12.67	0.08	74.65	12.57	0.03
Investment	7.17	0.00	79.58	13.20	0.04
Credit	27.35	0.50	61.64	10.31	0.21
Foreign Debt Share	9.99	0.08	77.40	12.49	0.04
Loan–Domestic Deposit Spread	1.36	0.01	84.31	14.24	0.09
Loan–Foreign Deposit Spread	0.63	0.02	84.93	14.34	0.07
Real Exchange Rate	1.95	0.02	85.69	12.32	0.02
CA Balance to GDP	3.61	0.04	82.63	13.50	0.23
Trade Balance to GDP	1.25	0.03	83.65	13.85	1.21
Inflation Rate	33.99	0.18	58.10	7.73	0.00
Policy Rate	24.07	0.08	67.12	8.73	0.01

exception being the spending shocks' declining effect on output as the horizon gets longer. These patterns are also confirmed for one-quarter- and one-year-ahead conditional variance decompositions (reported in table B1 in online appendix B). Notice that the variance decomposition analysis is sensitive to the calibrated size of individual shocks. However, it is informative in order to sharpen our focus on the importance of external shocks.

We further assess the quantitative performance of the calibrated model by analyzing impulse responses of model simulations to an exogenous increase in the country risk premium of 127 basis points, which is in the ballpark of what EMEs have experienced during the *taper tantrum* in May 2013. The solid lines in figure 2 are the impulse responses of model variables in the benchmark economy with the calibrated inflation targeting rule. The initial impact of the country borrowing premium shock is reflected on the real exchange rate in the direction of a sharp depreciation of 5 percent, which amplifies the increase in the cost of foreign borrowing. The resulting correction in the cyclical component of the ratio of current account balance to output is about 0.75 percent. In line with capital outflows, bankers' share of foreign debt declines more than 3 percent in eighteen quarters. The pass-through from increased nominal exchange rate depreciation leads to a rise in inflation by about 1 percentage point per annum. Banks cannot substitute domestic deposits for foreign funds easily, as domestic debt is more expensive than foreign debt on average. Therefore, bankers' demand for capital claims issued by non-financial firms collapses, which ignites a 1.5 percent decline in asset prices.

The fall in asset prices feeds back into the endogenous leverage constraint, (13), and hampers bank capital severely, an 11 percent fall on impact. The tightening financial conditions and declining asset prices in total reduce bank credit by 1.5 percent on impact, and amplify the decline in investment up to more than 3 percent and output up to 0.7 percent in five quarters. Observed surges in credit spreads over both domestic and foreign borrowing costs (by about 120 and 12 basis points per annum for loan–foreign deposits and loan–domestic deposits spreads, respectively) reflect the tightened financial conditions in the model. The decline in output and increase in inflation eventually calls for about 55 annualized basis points' increase in the short-term policy rate in the baseline economy.

Figure 2. Role of Asymmetric Frictions in the Decentralized Economy



Note: Impulse response functions are driven by a 127 annualized basis point increase in the country risk premium.

In conclusion, the model performs considerably well in replicating the adverse feedback loop (illustrated in figure 1) that EMEs fell into in the aftermath of the recent global financial crisis.

For brevity, we do not explain in detail here the impulse responses of model variables under the productivity, government spending, U.S. interest rate, and export demand shocks. Readers may refer to online appendix B to see the impulse response functions of model variables under each shock. However, we would like to note that most of the endogenous variables and the policy instruments respond to each shock in a fairly standard way, in line with the previous literature.

4.3 Asymmetric Financial Frictions and the UIP

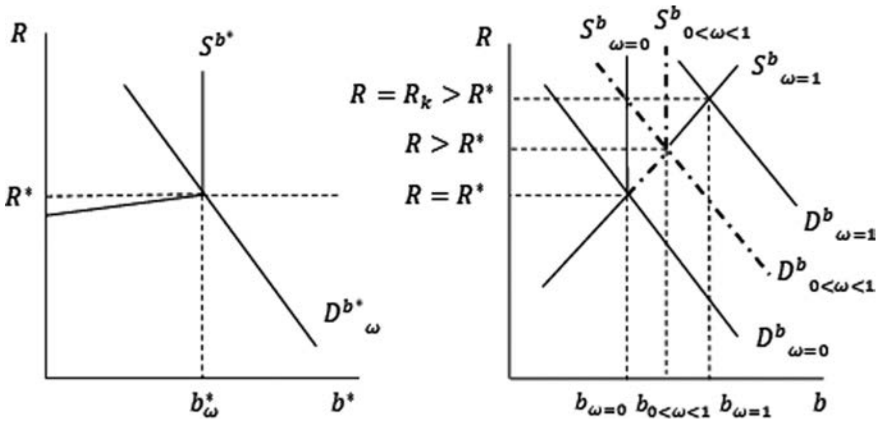
Under certain conditions, the UIP may not hold so that the exchange rate dynamics do not align with interest rate differentials.[10] In our framework, the agency problem between bankers and foreign lenders is asymmetrically more intense than that between bankers and domestic depositors, which creates a wedge between the real costs of domestic and foreign debt.[11] The analysis in online appendix A.2 delivers this result analytically by observing that, in equilibrium, the excess value of borrowing from abroad ν^* should be positive so that domestic depositors charge more than international lenders. In this regard, asymmetric financial frictions in a small open economy provide a microfoundation to stronger exchange rates than can be explained by the expected real interest rate differentials under the UIP as elaborated by Engel (2016).

Figure 3 provides a graphical illustration of the workings of the asymmetry in financial frictions. We plot the external funds market on the left panel of the figure, in which there is an almost perfectly elastic supply curve, and a downward-sloped demand curve for foreign funds, absent financial frictions. Indeed, the slope of the supply curve is slightly positive since the country risk premium increases

[10]See the *Handbook of International Economics* chapter by Engel (2014b), which lists a vast survey of contributions that consider departures from the UIP.

[11]Broner et al. (2014) show that when domestic borrowers discriminate against foreign creditors, a positive spread between domestic and foreign interest rates emerges. Fornaro (2015) obtains a similar result in a setup with collateral constraints by assuming that domestic borrowing does not require collateral.

Figure 3. Financial Frictions and Spreads



with the foreign debt. When $\lambda > 0$, the incentive compatibility constraint binds and imposes a leverage constraint on banks. Therefore, the supply curve of foreign debt makes a kink and becomes vertical at the equilibrium level of foreign debt b^*_{ω}.

The panel on the right displays the domestic funds market and covers three cases regarding the asymmetry in financial frictions. The supply curve in this market originates from the consumption–savings margin of households and is upward sloped. When $\omega_l = 0$, financial frictions are symmetric in both markets, and the supply curve makes a kink at the equilibrium domestic debt level $b_{\omega=0}$ and becomes vertical. This case corresponds to the UIP condition so that there is no arbitrage between the two sources of external finance, yielding $R_k > R = R^*$. When ω_l takes an intermediate value between zero and one, the demand schedule shifts to the right, as diverted assets constitute a smaller portion of total assets, making banks able to borrow more. This results in a movement along the workers' deposits supply curve until R takes an intermediate value between the loan rate and foreign borrowing rate $R_k > R > R^*$. Lastly, when $\omega_l = 1$, the domestic deposits market becomes frictionless and the deposit supply curve becomes continuous, rendering banks a veil from the perspective of households. In this case, $R_k = R > R^*$, implying that depositing at a financial intermediary is no different than directly investing in physical capital for households. This shifts the equilibrium level of domestic debt further to the right to $b_{\omega=1}$.

For simplicity, we did not plot the impact of changes in ω_l on the amount of foreign debt. Indeed, one shall expect that the share of foreign debt increases with ω_l despite the increase in domestic deposits. This is because ω_l levers up bankers so that it facilitates smaller amounts of domestic borrowing to bring enough relaxation of the financial constraint (7) in matching the excess cost of domestic debt.[12] Finally, in figure 2 we explore the impact of the asymmetry in financial frictions by using different ω_l values. The value of ω_l increases as we move along the dashed, solid, and dotted-solid lines in the figure in which the solid lines correspond to the benchmark economy. As expected, we find that the volatility of macroeconomic and financial variables, as well as monetary variables, gets smaller as the fraction of non-divertable domestic deposits increases.

4.4 Model Frictions and Optimal Monetary Policy

The model economy includes six key ingredients that generate deviations from a first-best flexible-price economy apart from the real rigidities such as habit persistence, variable capacity utilization, and investment adjustment costs. Among these, monopolistic competition and price rigidities are standard in canonical closed-economy New Keynesian models, whereas open-economy New Keynesian models additionally consider home bias and incomplete exchange rate pass-through.[13] These frictions distort the intratemporal consumption–leisure margin. Our model also includes credit frictions in the banking sector and a risk premium in the country borrowing rate. These additional frictions distort the intertemporal consumption–savings margin.

4.4.1 Intratemporal Wedge

In the closed, first-best flexible-price economy, the intratemporal efficiency requires that

[12] Steady-state comparisons for different levels of asymmetry confirm this conjecture that liability composition of bankers becomes more biased towards foreign debt as ω_l increases.

[13] Monacelli (2005), Faia and Monacelli (2008), and Galí (2008) elaborate on these distortions in New Keynesian models in greater detail.

$$\frac{MRS_t}{MPL_t} = \frac{-U_h(t)/U_c(t)}{W_t/P_t} = 1. \tag{16}$$

The model counterpart of the consumption–leisure margin is found by combining and manipulating equations (A2), (A8), (A22), (A23), and (A28) listed in online appendix A, which yields

$$\frac{MRS_t}{MPL_t} = \frac{-U_h(t)/U_c(t)}{W_t/P_t} = \frac{(p_t^H + \eta_t)}{X}, \tag{17}$$

with the expressions

$$p_t^H = \left[\frac{\omega}{1-(1-\omega)(p_t^F)^{(1-\gamma)}}\right]^{-\frac{1}{(1-\gamma)}}, \tag{18}$$

$$p_t^F = Xs_t + \frac{\varphi^F}{\epsilon-1}\frac{\pi_t^F(\pi_t^F-1)}{y_t^F} - \frac{\varphi^F}{\epsilon-1}E_t\left\{\Lambda_{t,t+1}\frac{\pi_{t+1}^F(\pi_{t+1}^F-1)}{y_t^F}\right\}, \tag{19}$$

$$X = \frac{\epsilon}{\epsilon-1}, \tag{20}$$

$$\eta_t = \frac{\varphi^H}{\epsilon-1}\frac{\pi_t^H(\pi_t^H-1)}{y_t^H} - \frac{\varphi^H}{\epsilon-1}E_t\left\{\Lambda_{t,t+1}\frac{\pi_{t+1}^H(\pi_{t+1}^H-1)}{y_t^H}\right\}. \tag{21}$$

The first expression, (18), is the relative price of home goods with respect to the aggregate price level, and it depends on ω, the home bias parameter. Under flexible home goods prices $\varphi^H = 0$, complete exchange rate pass-through $\varphi^F = 0$, and no monopolistic competition $X = 1$, the intratemporal wedge becomes $\frac{MRS_t}{MPL_t} = \frac{-U_h(t)/U_c(t)}{W_t/P_t} = p_t^H$. The case of $p_t^H < 1$ leads to an inefficiently low level of employment and output, as $\frac{MRS_t}{MPL_t} < 1$. The case of $\omega = 1$ corresponds to the closed economy in which the consumption basket only consists of home goods and $p_t^H = 1$, restoring intratemporal efficiency. Therefore, the Ramsey planner has an incentive to stabilize the fluctuations in p_t^H to smooth this wedge, which creates a misallocation between consumption demand and labor supply.

The second expression, (19), is the relative price of foreign goods with respect to the aggregate price level, which depends on the gross markup X, the real exchange rate s_t, and an expression representing incomplete exchange rate pass-through that originates from sticky import prices $\varphi^F > 0$. If import prices are fully flexible $\varphi^F = 0$, and there is perfect competition $X = 1$, then $p_t^F = s_t$ so that there is complete exchange rate pass-through. However, even if that is the case, the existence of the real exchange rate in the intratemporal efficiency condition still generates a distortion, depending on the level of home bias ω. The Ramsey planner would then want to contain fluctuations in the real exchange rate (which are equivalent to endogenous cost-push shocks as discussed by Monacelli 2005) to stabilize this wedge. Furthermore, if import prices are sticky $\varphi^F > 0$, the law-of-one-price gap might potentially reduce p_t^H below 1, creating an additional distortion in the intratemporal wedge. Therefore, optimal policy requires stabilization of the deviations from the law of one price, inducing smoother fluctuations in exchange rates.

The final expression, (21), stems from the price stickiness of home goods. Unless η_t is always equal to X, the intratemporal efficiency condition will not hold, leading to a welfare loss. $\eta_t = X$ for all t is not possible since price dispersion across goods, which depends on inflation, induces consumers to demand different levels of intermediate goods across time. Moreover, menu costs that originate from sticky home goods and import prices generate direct output losses. Consequently, the planner has an incentive to reduce inflation volatility, which helps contain the movements in the price dispersion.

Overall, in an open economy, price stability requires an optimal balance between stabilizing domestic markup volatility induced by monopolistic competition and sticky prices and containing exchange rate volatility induced by home bias and incomplete exchange rate pass-through.

4.4.2 Intertemporal Wedge

In the closed, first-best flexible-price economy with no financial frictions, the intertemporal efficiency requires that

$$\beta E_t R_{kt+1} \left[\frac{U_c(t+1)}{U_c(t)} \right] = 1. \tag{22}$$

Volatile credit spreads, the endogenous leverage constraint, fluctuations in the exchange rate, and the existence of country risk premium result in deviations of the model counterpart of the consumption–savings margin from what the efficient allocation suggests. Specifically, combining conditions (4), (A12), (A13), and (10) under no reserve requirements $rr_t = 0$ implies

$$\beta E_t R_{kt+1} \left[\frac{U_c(t+1)}{U_c(t)} \right] = (1 + \tau^1_{t+1} - \tau^2_{t+1}) > 1, \tag{23}$$

with the expressions

$$\tau^1_{t+1} = \frac{\left[\begin{array}{l} cov[\Xi_{t,t+1}, (R_{kt+1} - R_{t+1})] \\ \quad +cov[\Xi_{t,t+1}, (R_{t+1} - R^*_{t+1})] - \lambda \frac{\mu_t}{(1+\mu_t)} \end{array} \right]}{E_t[\Xi_{t,t+1}]} > 0, \tag{24}$$

$$\begin{aligned} \tau^2_{t+1} = {} & E_t[R^*_{nt+1}] E_t \left[\Psi_{t+1} \frac{S_{t+2}}{S_{t+1}} \frac{P_{t+1}}{P_{t+2}} \right] \\ & + cov \left\{ R^*_{nt+1}, \left[\Psi_{t+1} \frac{S_{t+2}}{S_{t+1}} \frac{P_{t+1}}{P_{t+2}} \right] \right\} < 0, \end{aligned} \tag{25}$$

where μ_t is the Lagrange multiplier of the incentive compatibility constraint faced by bankers and the signs of τ^1_{t+1} and τ^2_{t+1} are confirmed by simulations.

The first expression, τ^1_{t+1}, which contributes to the intertemporal wedge, originates from the financial frictions in the banking sector. In particular, the first term in τ^1_{t+1} is the risk premium associated with the credit spread over the domestic cost of borrowing, the second term is the risk premium associated with the funding spread, and the last term is the liquidity premium associated with binding leverage constraints of banks. When credit frictions are completely eliminated, $\lambda = 0$, both covariances and the last term in the numerator of τ^1_{t+1} become zero.[14] The Ramsey planner has an incentive

[14] When the UIP holds, $\omega_l = 0$, the second covariance disappears. Nevertheless, the overall wedge would increase substantially, since more of the total external finance can be diverted. On the other hand, when none of the domestic deposits are diverted, $\omega_l = 1$, the first covariance term disappears, leading the wedge to be smaller.

to contain the fluctuations in credit spreads over both domestic and foreign deposits to smooth this wedge by reducing movements in the Lagrange multiplier of the endogenous leverage constraint.

The second expression, τ_{t+1}^{2}, is the remaining part of the intertemporal wedge, stemming from openness and the country borrowing premium. The second term in this wedge is the risk premium associated with the U.S. interest rate and the real exchange rate movements. It is strictly negative because increases in the foreign interest rate R_{nt+1}^{*} reduce foreign borrowing and diminish the debt-elastic country risk premium Ψ_{t+1}. Furthermore, the magnitude of the real exchange rate depreciation gradually declines after the initial impact of shocks. Consequently, the optimal policy requires containing inefficient fluctuations in the exchange rate, which would reduce fluctuations in foreign debt and the country borrowing premium, accordingly. This channel is typically referred to as the financial channel by which exchange rate depreciation hurts the balance sheets of borrowers who suffer from liability dollarization, leading them to curb domestic demand as discussed by Kearns and Patel (2016).

Overall, in an open economy with financial frictions, financial stability requires an optimal balance between stabilizing credit spreads volatility induced by financial frictions, which distorts the dynamic allocation between savings and investment, and containing exchange rate volatility induced by openness, incomplete exchange rate pass-through and financial frictions, which leads to balance sheet deterioration. Therefore, the policymaker may want to deviate from fully stabilizing credit spreads by reducing the policy rate and resort to some degree of exchange rate stabilization by increasing the policy rate in response to adverse external shocks.

Finally, there exists an inherent tradeoff between price stability and financial stability. The policymaker may want to hike the policy rate in response to adverse external shocks to contain the rise in the inflation rate coming from the exchange rate depreciation and the fall in the production capacity of the economy at the expense of not being able to smooth fluctuations in lending spreads and to reduce the cost of funds for banks. Below we validate this discussion by solving the Ramsey planner's problem and quantitatively shed light on how she optimally balances the tensions across these tradeoffs.

Table 5. Steady States

Variable	Decentralized Economy	Ramsey Planner
Real Variables		
Output	0.7552	0.7569
Consumption	0.5731	0.5842
Investment	0.1447	0.1477
Hours Worked	0.3333	0.3328
Financial Variables		
Credit	2.7410	2.8220
Liability Composition (Foreign)	0.4083	0.1330
Leverage	7.9312	13.875
Asset Price	0.6627	0.6701
External Variables		
Real Exchange Rate	2.0894	2.0480
Trade Balance to GDP (%)	0.9136	0.2906
Monetary Variables		
Inflation Rate (% Annualized)	0	−0.5270
Markup	2.3530	2.2940
Real Money Balances	0.3357	0.3760

4.5 Long-Run and Cyclical Properties of the Decentralized and Ramsey Economies

We assume that the Ramsey planner chooses state-contingent allocations, prices, and policies to maximize lifetime utility of households, taking the private-sector equilibrium conditions (except the monetary policy rule) and exogenous stochastic processes $\{A_t, g_t^H, \psi_t, r_{nt}^*, y_t^*\}_{t=0}^{\infty}$ as given. She uses the short-term nominal interest rates as her policy tool to strike an optimal balance across different distortions analyzed in the previous section and can only achieve second-best allocations. We solve the optimal policy problem from a timeless perspective following Woodford (2003). We compute a second-order approximation to the solution of the Ramsey planner's problem.

We compare the non-stochastic steady states of decentralized and Ramsey economies in table 5 to understand the sources of long-run welfare costs. Most strikingly, the Ramsey planner reduces the exchange rate risk that bankers are exposed to by significantly lowering the ratio of foreign debt to total liabilities. This relaxes financial constraints of banks since domestic debt is diverted less. Consequently, the long-run levels of bank leverage, credit, investment, consumption, and output are higher in the Ramsey economy. In this regard, our work places in the strand of literature surveyed by Engel (2014a) that calls for a direct targeting of currency for financial stability goals as well as its indirect impact on inflation gap. Finally, the Ramsey steady state features a negative inflation rate of –0.52 percent per annum compared with the decentralized economy, which is calibrated to an inflation rate of zero.[15] This results in a lower steady-state markup and larger real money balances in the Ramsey economy with respect to the decentralized economy. Resembling the findings of Schmitt-Grohé and Uribe (2007), although the second-best economy exhibits deflation, we observe that the Ramsey steady state emerges closer to eliminating price rigidity rather than applying the Friedman rule, a deflation rate of 6.97 percent per annum in our case.

We then analyze the dynamics of the decentralized and Ramsey economies in order to gauge the source of short-run welfare costs. The intratemporal and intertemporal wedges in the model fluctuate due to movements in the credit spreads over domestic and foreign deposits, the real exchange rate, and the aggregate markup. Table 6 displays the relative volatilities of real, financial, external, and monetary variables in the decentralized and the planner's economies. The results suggest that the planner is able to smooth the fluctuations in variables that are related to the distortionary wedges. In particular, she reduces the relative volatilities of the CPI inflation, aggregate markup, and the real exchange rate by 68 percent, 36 percent, and 63 percent compared with the decentralized economy, respectively. Moreover, the planner is able to reduce the relative volatilities of lending spreads over domestic and foreign deposits by 10 percent and 62 percent relative to the decentralized economy, respectively. Taking these into account together with lower volatility in the real exchange rate, the results indicate that the planner is able to contain fluctuations in both wedges. Finally, we observe a substantial decline in the relative volatilities of bank leverage and bank net

[15] Schmitt-Grohé and Uribe (2007) find a Ramsey steady-state inflation of –0.55 percent per annum, which is fairly close to our case.

Table 6. Relative Volatilities

Variable	Decentralized Economy	Ramsey Planner
Real Variables		
Output	1.00	1.00
Consumption	0.70	0.70
Investment	4.93	5.06
Hours Worked	2.09	1.32
Financial Variables		
Credit	2.25	2.97
Liability Composition (Foreign)	1.95	4.42
Loan–Domestic Deposit Spread	0.20	0.18
Loan–Foreign Deposit Spread	0.37	0.14
Leverage	12.43	2.51
Net Worth	14.13	3.11
External Variables		
Real Exchange Rate	5.95	2.21
CA Balance to GDP	1.05	0.27
Trade Balance to GDP	0.33	0.32
Monetary Variables		
Inflation Rate	0.34	0.11
Policy Rate	0.11	0.25
Markup	7.97	5.13

worth, mainly due to the lower volatilities of lending spreads and the real exchange rate.

4.6 Welfare Analysis

We assess the performances of alternative policy regimes by calculating the welfare cost associated with a particular monetary policy rule relative to the time-invariant stochastic equilibrium of the Ramsey policy. Before going into the details of the welfare computation, we want to emphasize that our model economy features distortions due to monopolistic competition and financial frictions in the banking sector even at its non-stochastic steady state. Following Schmitt-Grohé and Uribe (2007), we do not assume any subsidy to factor inputs that removes the inefficiency introduced by monopolistic competition. In addition, the distortions due to credit frictions are also present at the deterministic steady state of the model. Therefore, we conduct our welfare analysis around a distorted steady state, and the constrained Ramsey planner can only achieve the second-best allocation.

Conducting welfare evaluations around an inefficient steady state requires us to implement a second-order approximation to the policy functions and the aggregate welfare in order to correctly rank alternative policy regimes and to obtain accurate welfare costs. Otherwise, aggregate welfare values would be the same across different policy rules since the mean values of endogenous variables are equal to their non-stochastic steady-state levels under a first-order approximation to the policy functions.

We first define the welfare associated with the time-invariant equilibrium associated with the Ramsey policy conditional on a particular state of the economy in period 0 as

$$V_0^R = E_0 \sum_{t=0}^{\infty} \beta^t U(c_t^R, h_t^R, m_t^R), \tag{26}$$

where E_0 denotes conditional expectation over the initial state, and c_t^R, h_t^R, and m_t^R stand for the contingent plans for consumption, labor, and real money balances under the Ramsey policy. Moreover, the welfare associated with the time-invariant equilibrium associated with a particular policy regime conditional on a particular state of the economy in period 0 is

$$V_0^A = E_0 \sum_{t=0}^{\infty} \beta^t U(c_t^A, h_t^A, m_t^A), \tag{27}$$

where c_t^A, h_t^A, and m_t^A stand for the contingent plans for consumption, labor, and real money balances under a particular alternative policy rule.

We then compute the welfare cost for each alternative monetary policy rule in terms of changes that compensate consumption variation relative to the Ramsey policy. Let λ^c stand for the welfare cost of implementing a particular monetary policy rule instead of the Ramsey policy conditional on a particular state in period 0. We define λ^c as the proportional reduction in the Ramsey planner's consumption plan that a household must forgo to be as well off under policy regime A. Therefore, λ^c is implicitly defined by

$$V_0^A = E_0 \sum_{t=0}^{\infty} \beta^t U\left((1-\lambda^c)c_t^R, h_t^R, m_t^R\right). \tag{28}$$

Hence, a positive value for λ^c implies that the Ramsey policy achieves a higher welfare relative to the particular policy regime.

Finally, we define aggregate welfare in the following recursive form to conduct a second-order approximation to V_0:

$$V_{0,t} = U(c_t, h_t, m_t) + \beta E_t V_{0,t+1}. \tag{29}$$

Schmitt-Grohé and Uribe (2007) show that V_0 can also be represented as

$$V_{0,t} = \overline{V_0} + \frac{1}{2}\Delta(V_0), \tag{30}$$

where $\overline{V_0}$ is the level of welfare evaluated at the non-stochastic steady state and $\Delta(V_0)$ is the constant correction term, denoting the second-order derivative of the policy function for $V_{0,t}$ with respect to the variance of shock processes. Therefore, equation (30) is an approximation of the welfare $V_{0,t}$, capturing the fluctuations of endogenous variables at the stochastic steady state.

4.7 Optimal Simple and Implementable Policy Rules

We search for optimal simple and implementable rules by following the methodology adopted by Schmitt-Grohé and Uribe (2007). Specifically, we run a discrete grid search for alternative optimal policy coefficients over the intervals $\rho_{r_n} \in [0, 0.995]$, $\varphi_\pi \in [1.001, 3]$, $\varphi_y \in [0, 3]$, $\varphi_f \in [-3, 3]$ for $f \in \{credit, q, spr, s, R_n^*\}$, $\rho_{rr} \in [0, 0.995]$, and $\varphi_{rr} \in [-3, 3]$. Each interval includes fifteen evenly distributed grid points except for the intervals for the response coefficients of external and financial variables as well as the interval for the response coefficient of the reserve requirement rule to credit spreads. Those intervals include thirty evenly distributed grid points since we span both positive and negative territories for their response coefficients. The boundary points of intervals are chosen by following the literature and respecting technical constraints. In particular, we confine the smoothing parameter of the interest rate rule to be positive and less than one to center our analysis on the optimal responses to inflation, output, and financial or external variables. We also choose the inertia parameter of the reserve requirement rule to be positive and less than one. The lower bound for inflation response is chosen to ensure determinacy. Following Schmitt-Grohé and Uribe (2007), the upper bounds of the remaining response coefficients are chosen arbitrarily, but in the interest of policymakers' convenience in communicating policy responses, they are fixed at arguably not very large magnitudes. We search for an optimal set of policy coefficients for each shock separately and under simultaneous shocks. The former experiment is informative for policymakers since it shows how the optimal set of policy coefficients changes with the underlying set of disturbances. However, the latter experiment might be more appealing in terms of actual policymaking because, in the real world, the monetary authority cannot perfectly disentangle the different sources of business cycle fluctuations. Section 4.8 covers optimal reserve requirement policies in addition to the interest rate policy. In the interest of space, we left the discussion of optimal policy responses to domestic shocks in isolation to online appendix C.

4.7.1 External Shocks

Table 7 displays the response coefficients of optimized conventional and augmented Taylor rules, the absolute volatilities of key macroeconomic variables under these rules, and the associated consumption-equivalent welfare costs relative to the Ramsey-optimal policy under country borrowing premium, the U.S. interest rate, and export demand shocks.

Optimized Taylor rules with and without smoothing feature no response to output variations under external shocks, with the exception of the rule without smoothing under export demand shocks. This confirms the results discussed by Schmitt-Grohé and Uribe (2007) that positive response to output is detrimental to welfare. The levels of the inflation coefficients, on the other hand, are at their lowest levels. This finding resembles the discussion of Aoki, Benigno, and Kiyotaki (2016) that in response to adverse external shocks (which already raise the cost of foreign debt) strong

Table 7. Optimal Simple Policy Rules under External Shocks

Country Risk Premium	ρ_{r_n}	φ_π	φ_y	φ_f	ρ_{rr}	φ_{rr}	σ_{r_n}	σ_π	σ_{spread}	σ_{RER}	σ_q	CEV(%)[a]
Optimized Taylor Rules (TR)												
Standard (without Smoothing)	–	1.0010	0	–	–	–	0.7878	1.4067	0.2464	7.3900	1.2141	4.5849
Standard (with Smoothing)	0.9950	1.0010	0	–	–	–	0.0032	0.4044	0.1129	6.0891	1.0429	0.2912
Optimized Augmented TR												
Credit	0.6396	1.0010	1.0714	−0.4286	–	–	0.5565	0.2489	0.8716	6.7310	5.0710	0.0096
Asset Price	0.6396	1.4294	0.6429	−1.0714	–	–	3.1285	0.6709	1.3206	7.4468	10.2921	0.0021
Credit Spread	0.9239	1.4294	0.4286	−2.1429	–	–	0.5134	1.1540	0.0265	6.9217	0.4592	0.0026
Real Exchange Rate	0.9950	1.0010	0.4286	3.0000	–	–	0.1381	0.1837	0.8079	5.8538	5.0637	0.0015
Optimized TR and RRR	0.3554	1.1438	2.3571	–	0.4264	−2.5714	0.2322	0.5677	0.0281	6.2455	0.9535	0.0006
Ramsey Policy	–	–	–	–	–	–	0.3610	0.0668	0.2211	3.3243	5.0007	0
U.S. Interest Rate	ρ_{r_n}	φ_π	φ_y	φ_f	ρ_{rr}	φ_{rr}	σ_{r_n}	σ_π	σ_{spread}	σ_{RER}	σ_q	CEV(%)[a]
Optimized Taylor Rules (TR)												
Standard (without Smoothing)	–	1.0010	0	–	–	–	0.3479	0.6212	0.1072	2.8912	0.5296	2.3948
Standard (with Smoothing)	0.9950	1.0010	0	–	–	–	0.013	0.1622	0.0427	2.3181	0.4070	1.7815
Optimized Augmented TR												
Credit	0.4975	1.0010	2.3571	−1.0714	–	–	0.8100	0.2149	0.4128	1.6112	2.6099	0.0011
Asset Price	0.2132	3.0000	2.1429	−2.1429	–	–	2.6984	0.1644	0.4259	3.2054	3.3204	0.0009
Credit Spread	0.9239	1.0010	3.0000	−3.0000	–	–	0.2784	0.5925	0.0123	2.7718	0.2092	0.0050
Real Exchange Rate	0.1421	1.2866	1.0714	1.2857	–	–	1.3936	0.3017	2.0838	4.1775	12.566	0.0025
U.S. Interest Rate	0.7818	1.0010	0	2.5714	–	–	0.9770	3.3691	2.2266	3.0112	13.368	0.0121
Optimized TR and RRR	0.4264	1.1438	1.9286	–	0.2843	−2.7857	0.0821	0.2120	0.0161	2.3449	0.3698	0.0004
Ramsey Policy	–	–	–	–	–	–	0.1333	0.0308	0.0901	1.3029	1.9737	0

(*continued*)

Table 7. (Continued)

Export Demand	ρ_{r_n}	φ_π	φ_y	φ_f	ρ_{rr}	φ_{rr}	σ_{r_n}	σ_π	σ_{spread}	σ_{RER}	σ_q	CEV(%)[a]
Optimized Taylor Rules (TR)												
Standard (without Smoothing)	–	3.0000	0.6429	–	–	–	0.0028	0.0084	0.0153	0.1041	0.0323	2.0777
Standard (with Smoothing)	0.9950	1.0010	0	–	–	–	0.0001	0.0049	0.0139	0.1058	0.0340	2.0769
Optimized Augmented TR												
Credit	0.9950	3.0000	0.6429	−2.7857	–	–	0.0298	0.2260	0.2939	0.5507	1.8000	0.0794
Asset Price	0.2843	1.0010	0.4286	−2.1429	–	–	0.9875	0.1947	0.2077	1.7078	1.2732	0.0047
Credit Spread	0.0711	1.0010	1.7143	−2.5714	–	–	0.4595	0.7643	0.0014	0.9428	0.2299	0.0001
Real Exchange Rate	0.2843	1.1438	0	1.7143	–	–	0.1597	0.0753	0.2641	0.2027	1.7710	0.0063
Optimized TR and RRR	0.9950	1.0010	1.7143	–	0.5686	−3.0000	0.0068	0.1101	0.0573	0.1529	0.8350	0.0021
Ramsey Policy	–	–	–	–	–	–	0.0062	0.0042	0.0140	0.0610	0.0564	0

[a]The reported welfare figures include both long-run and dynamic costs.

anti-inflationary stance of interest rate policy would hurt bank balance sheets even more by increasing the cost of domestic deposits. Since these policy rules do not target any financial stabilization objective, the volatilities of inflation, credit spreads, and the real exchange rate under these two optimized rules are much higher than those under the Ramsey policy, which justifies relatively higher welfare costs associated with these rules.

Table 7 indicates that under the country risk premium shock (the most relevant shock for EMEs, as discussed in section 4.2), the RER-augmented rule, which displays an aggressive and positive response to fluctuations in the real exchange rate and only mild responses to inflation and output variations, implies the largest welfare among all optimized *augmented* Taylor rules (the top panel). This optimal simple policy implies a welfare loss of 0.0015 percent vis-à-vis the Ramsey policy. This suggests that considering the financial channel for an EME central bank is crucial when domestic borrowers face currency mismatch. For this reason, the real exchange rate volatility is smaller under this rule than those implied by the other optimized Taylor rules. Since the central bank is already fighting the pass-through aggressively, it is not deemed useful to take a strong anti-inflationary stance. This is evident from the small degree of inflation volatility achieved under this rule. This finding is also linked to the insights discussed by Monacelli (2005, 2013) that under incomplete exchange rate pass-through, fluctuations in the exchange rate operate as endogenous cost-push shocks (see equation (19)) and optimal policy deviates from maintaining price stability towards exchange rate stability.

Lining up next is the optimized simple rule that augments asset prices. Our results confirm the findings of Faia and Monacelli (2007) that optimal policy calls for a negative response to asset prices together with a moderate anti-inflationary stance (with respective coefficients of –1.07 and 1.43). The welfare cost implied by this policy rule is 0.0021 percent against the Ramsey policy. While the absolute magnitude of the asset prices coefficient of optimal interest policy depends on the amplification created by financial frictions, the intuition behind its negative sign primarily hinges on the existence of investment adjustment costs. As discussed in online appendix A.3, capital producers buy the depreciated capital from intermediate goods firms and incur an investment adjustment cost that is scaled up by the asset price q. This causes Tobin's q to operate as a procyclical tax on investment and limits the expansion in investment to be smaller than the efficient magnitude in response to favorable shocks. Therefore, an *easing* in the policy rate boosts investment demand of intermediate goods producers and gets the dynamics of investment closer to the Ramsey allocation.[16] Stronger investment demand stimulated by the asset-price-augmented interest rate policy raises equilibrium asset prices more than the case with no policy response. Indeed, table 7 and figure 4 illustrate that both the Ramsey policy and the asset-price-augmented interest rate rule suggest a sharp increase in the volatility of asset prices.[17] Finally, the surge in demand by accommodative monetary policy calls for an increase in the inflation rate under this rule compared with the optimized standard Taylor rule (with respective coefficients of 1.43 and 1.001). Therefore, using an augmented policy rule with financial stability considerations allows the central bank to take a stronger anti-inflationary stance.

We find that the Taylor rule augmented by the loan–deposits spread achieves a level of welfare very close to that of the asset-price-augmented Taylor rule (the implied cost is 0.0026 percent). Interest rate policy features an LAW role in this case because credit spreads are countercyclical and the optimized augmented rule calls for an easing in bad times. Consequently, this rule justifies a higher inflation response coefficient than the optimized standard Taylor rule. Under this rule, the volatility of credit spreads is even lower than that in the Ramsey policy whereas the volatilities of the inflation rate and the real exchange rate are much higher.

Our findings also show that optimized credit-augmented interest rate rules feature a negative response to the level of credit. This

[16] Our results seem to contrast with the findings of Gambacorta and Signoretti (2014), who find that an interest rate policy rule that is augmented with a positive response to asset prices performs better than a standard Taylor rule. However, they do not consider the negative range for the asset price response coefficient while searching for policy rules that minimize loss functions, which depend on inflation and output variability. Indeed, they obtain the minimum loss levels when this coefficient hits its lower bound of zero.

[17] This insight is akin to the Ramsey planner's optimal policy of increasing volatility in labor income tax rate under the existence of labor market distortions in order to bring fluctuations in employment closer to the efficient fluctuations. For a detailed elaboration, see Arseneau and Chugh (2012).

result is mainly due to the fact that the decentralized economy in the model features underborrowing rather than overborrowing compared to the Ramsey planner's economy as in Benigno et al. (2013). These authors show that introducing production might transform the *overborrowing* observed in endowment economies to *underborrowing*, which in turn suggests that macroprudential taxes that are intended to reduce borrowing are detrimental to welfare. Our steady-state comparisons that are reported in table 5 confirm this underborrowing result. The table shows that the planner's economy features a higher leverage than the decentralized economy. How the planner achieves a higher leverage hinges on the asymmetric financial frictions on the funding side of the banks. In particular, the type of externality that makes the market optimal constrained efficient is a funding externality that arises due to the asymmetry in the rates of diversion between domestic and foreign borrowing of the banking sector where domestic borrowing is diverted less and foreign borrowing is diverted more. Therefore, a higher domestic borrowing or a lower foreign borrowing by banks relaxes their financial constraints more. The planner exploits this feature and induces banks to collect more domestic deposits rather than foreign funds to relax their borrowing constraints. This results in a higher leverage and a lower net worth in the planner's economy. A lower net worth also implies that the planner uses the nominal interest rate to indirectly tax the rents of bankers. Overall, the Ramsey planner uses the nominal interest rate to mitigate the funding externality in the banking sector to extend more credit to non-financial firms, leading to more capital accumulation, higher investment, and thus higher output in the economy. In endowment economies, this production (and capital accumulation) channel does not exist. In this environment, an optimized credit-augmented monetary policy rule reduces the policy rate in response to positive deviations of credit from its steady-state level over the business cycle. This further increases deposit issuance and credit extension, stimulates investment more, and finally increases output. Reducing policy rate in response to higher credit brings allocations in the decentralized economy closer to those in the second-best economy (i.e., the Ramsey planner's economy). This finding is consistent with that discussed by Benigno et al. (2013) since the macroprudential tax on borrowing in their paper is akin to a policy rate hike in our model, which increases the cost of borrowing for banks. While the optimized credit-augmented interest rules achieve a higher level of welfare than do the optimized standard Taylor rules, their implied welfare cost is larger than those of the optimized RER- or credit-spread-augmented interest rate rules.

Optimized augmented Taylor rules under the U.S. interest and export demand shocks display very similar results as in the case of the country borrowing premium shocks. For brevity, we do not discuss the results here in detail. We just would like to focus on the results of a particular augmented Taylor rule. Specifically for the U.S. interest rate shocks, we also consider another optimized augmented Taylor rule that directly responds to the U.S. policy rate movements in addition to inflation and output variations. This rule is of particular interest for EME policymakers, as domestic policy rates in EMEs might be driven by the changes in the U.S. policy rate over and above domestic factors would imply, which is also empirically shown by Takáts and Vela (2014) and Hofmann and Takáts (2015). The latter paper suggests two reasons as to why EME policy rates might follow those in the United States. First, they might want to eliminate high interest differentials resulting from the U.S. policy rate movements, which may potentially cause exchange rate appreciation and hence a deterioration in trade competitiveness. Second, they might want to prevent excessive short-term capital inflows by eliminating large interest rate differentials in order to maintain financial stability. The model results *qualitatively* confirm their empirical findings, suggesting that it is optimal for an EME policymaker to positively respond to the U.S. policy rate. In response to an orthogonalized 100 basis point increase in the U.S. policy rate, we find that the EME central bank should raise its policy rate by 257 basis points. However, the welfare cost implied by this policy rule is an order of magnitude larger than those implied by the credit spread and the RER-augmented Taylor rules. On the other hand, when compared with the optimized standard Taylor rule with smoothing, the welfare cost implied by this policy is much smaller (0.0121 percent versus 1.7815 percent).

4.7.2 All Shocks

Table 8 displays the response coefficients of optimized conventional and augmented Taylor rules, the absolute volatilities of key

Table 8. Optimal Simple Policy Rules under All Shocks

All Shocks	ρ_{r_n}	φ_π	φ_y	φ_f	ρ_{rr}	φ_{rr}	σ_{r_n}	σ_π	σ_{spread}	σ_{RER}	σ_q	CEV(%)[a]
Optimized Taylor Rules (TR)												
Standard (without smoothing)	–	1.0010	0	–	–	–	0.9424	1.6829	0.2734	7.9497	1.3517	6.0616
Standard (with Smoothing)	0.9239	1.0010	0	–	–	–	0.0614	0.5532	0.1757	6.5809	1.3472	2.1345
Optimized Augmented TR												
Credit	0.9239	1.0010	1.7143	−0.6429	–	–	0.2401	0.3229	0.7744	6.4310	4.7299	0.0450
Asset Price	0.8529	2.4289	1.9286	−2.7857	–	–	3.8831	0.9414	0.8868	10.716	11.529	0.0013
Credit Spread	0.9950	1.0010	2.7857	−1.500	–	–	0.0908	0.5682	0.0579	6.7198	0.8986	0.0027
Real Exchange Rate	0.9950	1.0010	0.4286	2.7857	–	–	0.1391	0.3735	0.8674	6.3262	5.3979	0.0093
U.S. Interest Rate	0.9239	1.0010	0	0.2143	–	–	0.0593	0.5302	0.2976	6.5545	1.9367	0.1332
Optimized TR and RRR	0.5686	1.4294	2.1429	–	0.3554	−1.7143	0.4565	0.9267	0.3220	6.6794	1.9311	0.0040
Ramsey Policy	–	–	–	–	–	–	0.4460	0.1861	0.2472	3.8810	5.4933	0

[a]The reported welfare figures include both long-run and dynamic costs.

macroeconomic variables under these rules, and the associated consumption-equivalent welfare costs relative to the optimal Ramsey policy under domestic (TFP and government spending) and external shocks hitting the economy simultaneously.

The optimized Taylor rules with and without smoothing still display zero response to output deviations under all shocks. The magnitudes of the inflation response coefficients are at their lower bounds, and the optimized standard Taylor rule with smoothing still features a high degree of inertia. Furthermore, these two optimized rules imply much more volatility in the CPI inflation rate and the RER together with much less volatility in asset prices in comparison with the Ramsey policy, which explains relatively higher welfare losses associated with these rules.

The findings associated with the optimized augmented Taylor rules suggest that a strong negative response to asset prices together with an aggressive response to inflation achieves the highest welfare possible. The associated welfare cost vis-à-vis the Ramsey policy is 0.0013 percent. It appears that the gains are mainly linked to stimulating investment demand, as this policy generates more asset price volatility than that implied by the Ramsey policy. What follows the asset-price-augmenting rule is the optimal rule that negatively responds to the credit spreads with an implied welfare cost of 0.0027 percent. As in the case of external shocks, the gains associated with this rule depend on the significant reduction in the volatility of credit spreads. Finally, we observe that the RER-augmented Taylor rule implies a welfare cost in the same order of magnitude as the aforementioned policies (0.0093 percent) and suggests a positive response to fluctuations in the real exchange rate with a mild anti-inflationary stance. We also confirm our previous findings under other external shocks that it is optimal to negatively respond to the level of credit and positively respond to the U.S. interest rates, whereas these policy rules are dominated by the asset-price-augmented interest rate policy. Nevertheless, we find that in response to a 100 basis point increase in the U.S. policy rate, the EME policy rate should be raised by 21 basis points (under simultaneous shocks), which is *quantitatively* in line with the empirical findings of Hofmann and Takáts (2015).

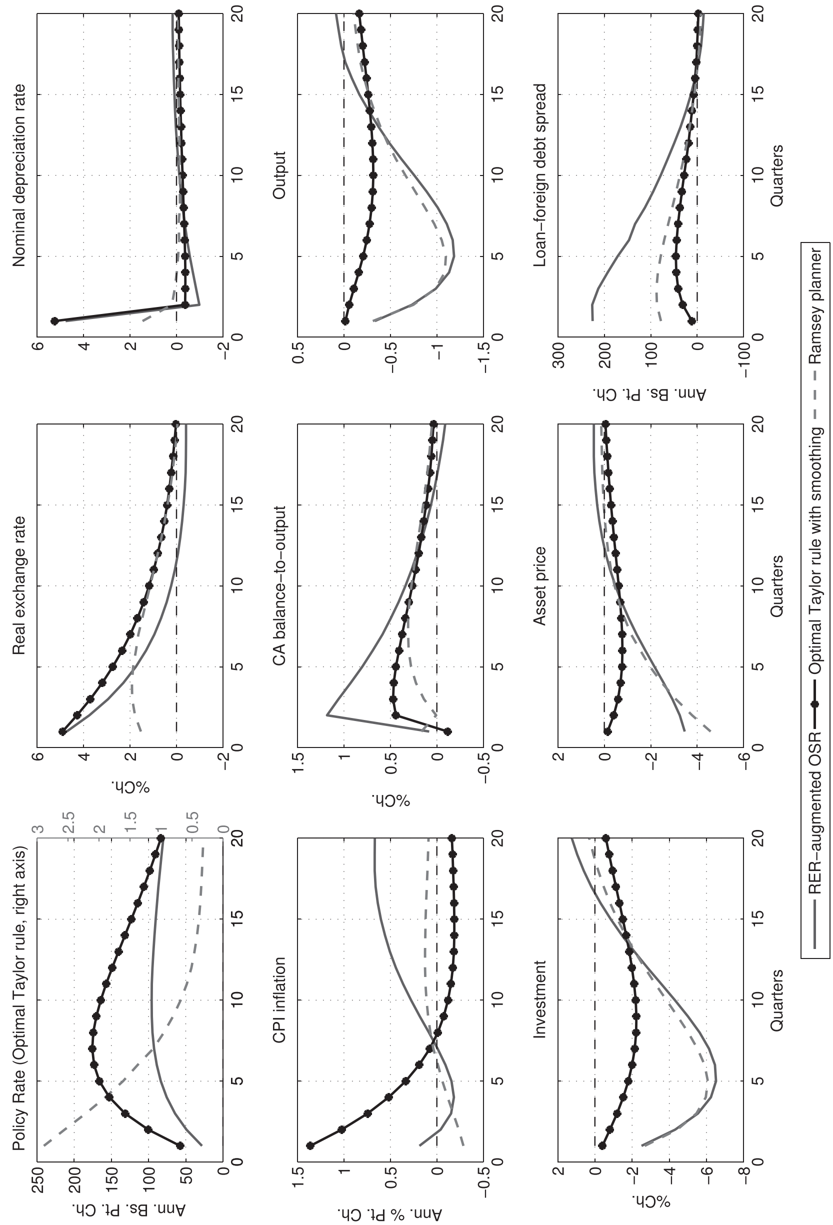
4.7.3 Optimal Policy Rules versus Ramsey-Optimal Policy

Figure 4 compares the impulses responses to a one-standard-deviation country risk premium shock under the Ramsey planner's economy (dashed plots) with the selected optimal simple interest rate rules. In particular, we select the optimal real-exchange-rate-augmented interest rate rule (straight plots) since it produces the smallest welfare cost vis-à-vis the Ramsey-optimal policy and the optimal standard Taylor rule with smoothing (straight plots with asterisks) in order to highlight the departures of *conventional wisdom* from optimality in our setup. We highlight the country risk premium shock due to its strong explanatory power that emerged in the variance decomposition analysis. For brevity, we do not plot the impulse responses to other domestic or external shocks, which are available from the authors upon request.

The planner increases the policy rate by about 250 basis points per annum on impact in response to a 127 basis point annualized increase in the country borrowing premium. Accordingly, both the nominal and real exchange rates depreciate only about 2 percent, which contains the pass-through to CPI inflation via imported goods. As a result, the annual CPI inflation rate *falls* one-quarter of a percentage point on impact in the planner's economy, while it increases by 1 percentage point in the decentralized economy (see straight plots in figure 2). The Ramsey planner also contains inefficient movements in the credit spreads over the cost of foreign debt and ensures that the credit spreads increase by less than 100 basis points in annualized terms. This enables the planner to substantially reduce the reversal in the current account balance. Notice that the second-best equilibrium warrants increased volatility in asset prices and investment compared with the decentralized economy. In that respect, the Ramsey planner trades off a smoother path of the real exchange rate and credit spreads against a more volatile trajectory for investment and output in order to achieve a more stable path of the CPI inflation rate.

The optimal RER-augmented rule calls for an increase of 30 basis points in the policy rate in annualized terms under the country borrowing premium shock. This results in 3 percent more depreciation in the real exchange rate and a 1 percentage point higher increase in the inflation rate compared with the Ramsey-optimal policy. As

Figure 4. Optimal Simple Rules vs. Ramsey Planner under Country Risk Premium Shocks



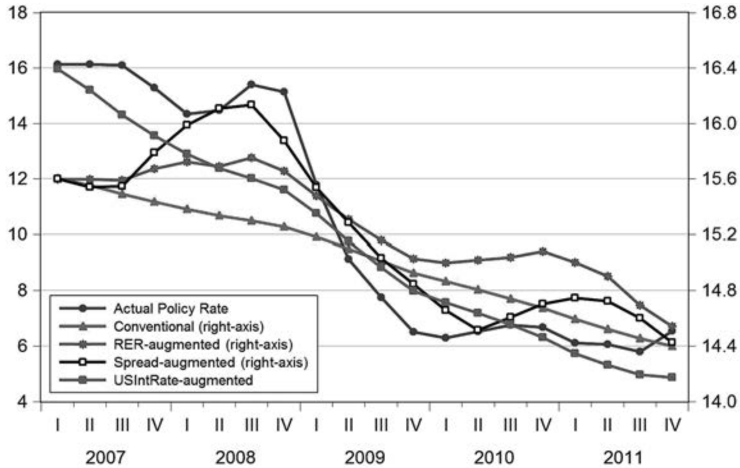
a result, credit spreads rise more and there is a stronger reversal in the current account balance in comparison with the second-best economy. However, this optimized rule approximates the Ramsey-optimal policy fairly well in terms of bringing fluctuations in the asset price, investment, and output closer to efficient fluctuations. Recall that the real exchange rate response coefficient of this optimized rule hits its upper bound of 3 (see the top panel of figure 7), suggesting that this policy could approximate the Ramsey-optimal policy even better should we allow the response coefficient to take a larger value.

Since the optimal Taylor rule with smoothing exhibits no response to the real exchange rate and displays only a mild response to inflation, it calls for a negligible rise (by about only 2 basis points per annum) in the short-term policy rate when the country risk premium shock hits the economy. While the on-impact depreciation under this rule resembles that implied by the optimal RER-augmented rule, currency exchanges at about a 1 percent more depreciated level under this rule for twelve consecutive quarters. This results in a 1.4 percentage point rise in the CPI inflation rate on impact due to the pass-through and underpins the relatively larger welfare loss implied by this rule. Since the tightening in the policy rate is much smaller under this rule, credit spreads rise even less than under the Ramsey-optimal policy. Consequently, the dynamics of investment and asset prices implied by this rule deviate substantially from those produced by either the second-best economy or the optimal exchange-rate-augmented policy.

4.7.4 Optimal Policy Rules versus Data

Figure 5 illustrates the comparison of trajectories for the optimal simple and implementable short-term policy rules with the empirical trajectory of the policy rate determined by the CBRT. In order to obtain the model-implied trajectories, we feed in the empirical time series for policy targets into the optimized augmented Taylor rules. We find that a combination of the optimized U.S. interest-rate- and credit-spread-augmented interest rate rules resembles the actual policy rate fairly well. In particular, the former (the plot with full squares) captures the trend of the empirical series, while the latter (the plot with empty squares) captures its cyclical properties. Recall

Figure 5. Optimal and Empirical Interest Rate Trajectories



that the optimal standard Taylor rule (the plot with triangles) is not successful in capturing either the absolute level or the cyclicality of the empirical time series of the short-term policy rate.

4.8 Optimal Interest Rate and Reserve Requirement Policies

Augmenting the interest rate policy with an LAW goal might be cumbersome for a central bank if it aims to simultaneously achieve price and financial stability targets, which imply different trajectories for interest rates in certain cases. To that end, Shin (2013) and Chung et al. (2014) emphasize the usefulness of liability-based policy tools, such as reserve requirements, in meeting financial stability targets alongside conventional monetary policy.[18] In addition, Cordella et al. (2014) provide empirical evidence on the use of reserve requirements as a countercyclical monetary policy tool in developing

[18]Instead of using reserve requirements additionally, one might also consider a single optimal tool, the short-term interest rate, augmenting a few financial response variables, simultaneously. Although the practical implementability of such a policy would arguably be cumbersome, we think that such a policy would move in the direction implied by our overall analysis in regards to the augmenting variables that we consider.

countries. They emphasize that due to the procyclical behavior of the exchange rate over the business cycle in developing countries, the countercyclical use of interest rates proves to be complicated due to its impact on the exchange rate. In this regard, reserve requirements can be useful as a second policy tool in response to capital inflows or outflows.

In this section, we aim to address these issues by operationalizing reserve requirements as a policy rule that tries to smooth out fluctuations in credit spreads over the cost of foreign borrowing together with a typical short-term policy rate. We then examine whether the optimal mix of this time-dependent rule with a conventional Taylor rule can compete with an optimal LAW-type monetary policy rule in maximizing household welfare. The seventh row in each panel of tables 7 and 8 reports the optimal simple interest rate and reserve requirement rule mix that is pinned down by using a similar methodology to that in the previous section. Specifically, we jointly optimize one persistence coefficient for each policy tool, the inflation and output response coefficients of the interest rate policy, and the credit spread response coefficient of the reserve requirement rule.

Two important results stand out. First, under domestic, external, and all shocks, we always find a negative response of reserve requirements to the credit spreads over the cost of foreign debt. That is, the central bank uses this tool to LAW. Consequently, the welfare costs compared with the Ramsey policy always emerge as strictly smaller than that implied by the optimized simple Taylor rule, which does not LAW. This is because the reserve requirement rule calls for a decline in the effective tax levied on banks' external finance in bad times, since credit spreads are countercyclical. This partly offsets the negative impact of declining asset prices and depreciating exchange rate on the balance sheet of banks, and reduces the welfare cost obtained under the standard Taylor rule. Thus, as expected, the results suggest that employing the two rules in response to multiple wedges is better than using only the short-term policy rate, which does not LAW.

Second, under country risk premium shocks, the jointly optimized Taylor and reserve requirement rules attain a smaller welfare cost (0.0006 percent) than the best optimized augmented interest rate rule, which responds to the real exchange rate (0.0015 percent). This result derives from the fact that the jointly optimized Taylor and reserve requirement rules reduce the volatility of credit spreads an order of magnitude more than the real-exchange-rate-augmented Taylor rule. In addition, this policy mix performs fairly well under domestic, other external, and all shocks. This suggests that should the central bank find it hard to introduce an LAW role for the short-term interest policy, it might rely on the use of reserve requirements as an additional tool without forgoing substantial stabilization gains.

5. Conclusion

This paper contributes to the previous literature by investigating the quantitative performances of LAW-type monetary policy rules and reserve requirement policies in mitigating the negative impact of external shocks on macroeconomic or financial stability. To this aim, we build a New Keynesian small open-economy model that includes a banking sector with domestic and foreign borrowing and for which external and financial conditions influence macroeconomic dynamics. We show that the model is reasonably successful in explaining the observed dynamics of the adverse macrofinancial feedback loop that EMEs endured during and after the global financial crisis. On the normative side, we take the Ramsey equilibrium as a benchmark and search for optimal, simple, and implementable short-term interest rules that aim at minimizing welfare losses against the planner's economy.

Our analysis highlights three main results. First, we find that the optimized augmented monetary policy rules—in particular, the policy rate specifications that respond to the real exchange rate, asset prices, and credit spreads in addition to inflation and output gaps—outperform the optimized standard Taylor rules under both domestic and external shocks. In addition, the optimized standard Taylor rule displays at best a mild anti-inflationary stance. This finding supports the idea that it might be desirable to deviate from price stability in favor of external or financial stability in small open economies. Second, we show that interest rate policy usually displays a stronger anti-inflationary stance when financial stability considerations are addressed by monetary policy. Lastly, we find that an optimized policy mix that comprises a reserve requirement rule (which responds to credit spreads) and a standard Taylor rule improves upon an optimized standard Taylor rule under both domestic and external shocks.

We abstract from irrational exuberance or asset price bubbles. The framework might be extended in those dimensions to explore any macroprudential role for LAW-type interest rate rules or countercyclical reserve requirements in a gradual buildup of macrofinancial risks. Lastly, future research might consider an explicit account of non-financial firms' balance sheets to study how the policy prescriptions of the model are affected by this additional source of financial amplification.

References

Akinci, O., and A. Queralto. 2014. "Banks, Capital Flows and Financial Crises." International Finance Discussion Paper No. 1121, Board of Governors of the Federal Reserve System.

Angelini, P., S. Neri, and F. Panetta. 2011. "Monetary and Macroprudential Policies." Economic Working Paper No. 801, Bank of Italy.

Angeloni, I., and E. Faia. 2013. "Capital Regulation and Monetary Policy with Fragile Banks." *Journal of Monetary Economics* 60 (3): 311–24.

Aoki, K., G. Benigno, and N. Kiyotaki. 2016. "Monetary and Financial Policies in Emerging Markets." Unpublished Manuscript.

Arseneau, D. M., and S. K. Chugh. 2012. "Tax Smoothing in Frictional Labor Markets." *Journal of Political Economy* 120 (5): 926–85.

Bahadir, B., and I. Gumus. 2014. "Credit Decomposition and Business Cycles in Emerging Market Economies." Unpublished Manuscript.

Benigno, G., H. Chen, C. Otrok, A. Rebucci, and E. R. Young. 2013. "Financial Crises and Macro-prudential Policies." *Journal of International Economics* 89 (2): 453–70.

Bernanke, B. S., M. Gertler, and S. Gilchrist. 1999. "The Financial Accelerator in a Quantitative Business Cycle Framework." In *Handbook of Macroeconomics*, Vol. 1C, ed. J. B. Taylor and M. Woodford, 1341–93 (chapter 21). North-Holland.

Broner, F., A. Erce, A. Martin, and J. Ventura. 2014. "Sovereign Debt Markets in Turbulent Times: Creditor Discrimination and

Crowding-out Effects." *Journal of Monetary Economics* 61 (1): 114–42.

Christiano, L. J., M. Eichenbaum, and C. L. Evans. 2005. "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy." *Journal of Political Economy* 113 (1): 1–45.

Chung, K., J.-E. Lee, E. Loukoianova, H. Park, and H. S. Shin. 2014. "Global Liquidity through the Lens of Monetary Aggregates." IMF Working Paper No. 14/9.

Cordella, T., P. Federico, C. Vegh, and G. Vuletin. 2014. "Reserve Requirements in the Brave New Macroprudential World." Policy Research Working Paper No. 6793, World Bank.

Cúrdia, V., and M. Woodford. 2010. "Credit Spreads and Monetary Policy." *Journal of Money, Credit and Banking* 42 (s1): 3–35.

Ehlers, T., and A. Víllar. 2015. "The Role of Banks." *BIS Papers* 83 (November): 9–39.

Engel, C. 2014a. "Exchange Rate Stabilization and Welfare." *Annual Review of Economics* 6: 155–77.

———. 2014b. "Exchange Rates and Interest Parity." In *Handbook of International Economics*, Vol. 4, ed. G. Gopinath, E. Helpman, and K. Rogoff, 453–522 (chapter 8). Elsevier.

———. 2016. "Exchange Rates, Interest Rates, and the Risk Premium." *American Economic Review* 106 (2): 436–74.

Faia, E., and T. Monacelli. 2007. "Optimal Interest Rate Rules, Asset Prices, and Credit Frictions." *Journal of Economic Dynamics and Control* 31 (10): 3228–54.

———. 2008. "Optimal Monetary Policy in a Small Open Economy with Home Bias." *Journal of Money, Credit and Banking* 40 (4): 721–50.

Fornaro, L. 2015. "Financial Crises and Exchange Rate Policy." *Journal of International Economics* 95 (2): 202–15.

Galí, J. 2008. *Monetary Policy, Inflation, and the Business Cycle: An Introduction to New Keynesian Framework.* Princeton, NJ: Princeton University Press.

Galí, J., and T. Monacelli. 2005. "Monetary Policy and Exchange Rate Volatility in a Small Open Economy." *Review of Economic Studies* 72 (3): 707–34.

Gambacorta, L., and F. M. Signoretti. 2014. "Should Monetary Policy Lean Against the Wind? An Analysis Based on a DSGE

Model with Banking." *Journal of Economic Dynamics and Control* 43 (June): 146–74.

Gertler, M., S. Gilchrist, and F. Natalucci. 2007. "External Constraints on Monetary Policy and the Financial Accelerator." *Journal of Money, Credit and Banking* 39 (2/3): 295–330.

Gertler, M., and N. Kiyotaki. 2011. "Financial Intermediation and Credit Policy in Business Cycle Analysis." In *Handbook of Macroeconomics,* Vol. 3A, ed. B. M. Friedman and M. Woodford, 547–99 (chapter 11). North-Holland.

Gilchrist, S., and E. Zakrajšek. 2011. "Monetary Policy and Credit Supply Shocks." *IMF Economic Review* 59 (2): 195–232.

Glocker, C., and P. Towbin. 2012. "Reserve Requirements for Price and Financial Stability: When Are They Effective?" *International Journal of Central Banking* 8 (1): 65–113.

Hirakata, N., N. Sudo, and K. Ueda. 2013. "Capital Injection, Monetary Policy, and Financial Accelerators." *International Journal of Central Banking* 9 (2): 101–45.

Hofmann, B., and E. Takáts. 2015. "International Monetary Spillovers." *BIS Quarterly Review* (September): 105–18.

Iacoviello, M., and S. Neri. 2010. "Housing Market Spillovers: Evidence from an Estimated DSGE Model." *American Economic Journal: Macroeconomics* 2 (2): 125–64.

Kearns, J., and N. Patel. 2016. "Does the Financial Channel of Exchange Rates Offset the Trade Channel?" *BIS Quarterly Review* (December): 95–113.

Kolasa, M., and G. Lombardo. 2014. "Financial Frictions and Optimal Monetary Policy in an Open Economy." *International Journal of Central Banking* 12 (1): 43–94.

Medina, J. P., and J. Roldós. 2014. "Monetary and Macroprudential Policies to Manage Capital Flows." IMF Working Paper No. 14/30.

Mihaljek, D. 2010. "Domestic Bank Intermediation in Emerging Market Economies during the Crisis: Locally Owned versus Foreign-owned Banks." *BIS Papers* 54 (December): 31–48.

Mimir, Y., T. Taşkın, and E. Sunel. 2013. "Required Reserves as a Credit Policy Tool." *B.E. Journal of Macroeconomics* 13 (1): 823–80.

Monacelli, T. 2005. "Monetary Policy in a Low Pass-Through Environment." *Journal of Money, Credit and Banking* 37 (6): 1047–66.

———. 2013. "Is Monetary Policy in an Open Economy Fundamentally Different?" *IMF Economic Review* 61 (1): 6–21.

Notarpietro, A., and S. Siviero. 2015. "Optimal Monetary Policy Rules and House Prices: The Role of Financial Frictions." *Journal of Money, Credit and Banking* 47 (s1): 383–410.

Obstfeld, M. 2015. "Trilemmas and Trade-offs: Living with Financial Globalisation." BIS Working Paper No. 480.

Rey, H. 2015. "Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence." NBER Working Paper No. 21162.

Rotemberg, J. J. 1982. "Sticky Prices in the United States." *Journal of Political Economy* 90 (6): 1187–1211.

Schmitt-Grohé, S., and M. Uribe. 2003. "Closing Small Open Economy Models." *Journal of International Economics* 61 (1): 163–85.

———. 2007. "Optimal Simple and Implementable Monetary and Fiscal Rules." *Journal of Monetary Economics* 54 (6): 1702–25.

Shin, H. S. 2013. "Adapting Macro Prudential Approaches to Emerging and Developing Economies." In *Dealing with the Challenges of Macro Financial Linkages in Emerging Markets,* ed. O. Canuto and S. Ghosh, 17–56 (chapter 1). Washington D.C.: World Bank.

Smets, F., and R. Wouters. 2007. "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach." *American Economic Review* 97 (3): 586–606.

Takáts, E., and A. Vela. 2014. "International Monetary Policy Transmission." *BIS Papers* 78 (August): 51–70.

Uribe, M., and V. Yue. 2006. "Country Spreads and Emerging Countries: Who Drives Whom?" *Journal of International Economics* 69 (1): 6–36.

Woodford, M. 2003. *Interest and Prices: Foundations of a Theory of Monetary Policy.* Princeton, NJ: Princeton University Press.

Online Appendixes to External Shocks, Banks, and Optimal Monetary Policy: A Recipe for Emerging Market Central Banks*

Yasin Mimir[a] and Enes Sunel[b]
[a]Norges Bank
[b]Sunel & Sunel Law Firm

Appendix A. Model Derivations

A.1 Households

There is a large number of infinitely lived identical households, which derive utility from consumption c_t, leisure $(1 - h_t)$, and real money balances $\frac{M_t}{P_t}$. The consumption good is a constant-elasticity-of-substitution (CES) aggregate of domestically produced and imported tradable goods as in Galí and Monacelli (2005) and Gertler, Gilchrist, and Natalucci (2007),

$$c_t = \left[\omega^{\frac{1}{\gamma}}(c_t^H)^{\frac{\gamma-1}{\gamma}} + (1-\omega)^{\frac{1}{\gamma}}(c_t^F)^{\frac{\gamma-1}{\gamma}}\right]^{\frac{\gamma}{\gamma-1}}, \tag{A1}$$

*We would like to thank Leonardo Gambacorta, Nobuhiro Kiyotaki, Giovanni Lombardo, Hyun Song Shin, Philip Turner, the seminar participants at the Bank for International Settlements, Norges Bank, the Georgetown Center for Economic Research Biennial Conference 2015, the CBRT-BOE Joint Workshop 2015 on “The International Monetary and Financial System — Long-term Challenges, Short-term Solutions,” the 21st International Conference on Computing in Economics and Finance, the 11th World Congress of the Econometric Society, and the 47th Money, Macro and Finance Research Group Annual conference for their helpful comments and suggestions. This paper circulated earlier under the title “External Shocks, Banks and Optimal Monetary Policy in an Open Economy.” Yasin Mimir completed this project while visiting the Bank for International Settlements under the Central Bank Research Fellowship program. The views expressed in this paper are those of the authors only and do not necessarily reflect the views of Norges Bank or of the Bank for International Settlements (BIS). The usual disclaimer applies. Corresponding author: Yasin Mimir, Norges Bank, Monetary Policy Department, Bankplassen 2, 0151 Oslo, Norway; Tel.: +4722316811; E-mail: yasin.mimir@norges-bank.no; Personal homepage: http://www.yasinmimir.com.

where $\gamma > 0$ is the elasticity of substitution between home and foreign goods, and $0 < \omega < 1$ is the relative weight of home goods in the consumption basket, capturing the degree of home bias in household preferences. Let P_t^H and P_t^F represent domestic-currency-denominated prices of home and foreign goods, which are aggregates of a continuum of differentiated home and foreign good varieties, respectively.

The expenditure minimization problem of households

$$\min_{c_t^H, c_t^F} P_t c_t - P_t^H c_t^H - P_t^F c_t^F$$

subject to (A1) yields the demand curves $c_t^H = \omega \left(\frac{P_t^H}{P_t}\right)^{-\gamma} c_t$ and $c_t^F = (1-\omega)\left(\frac{P_t^F}{P_t}\right)^{-\gamma} c_t$ for home and foreign goods, respectively.

The final demand for home consumption good c_t^H is an aggregate of a continuum of varieties of intermediate home goods along the [0,1] interval. That is, $c_t^H = \left[\int_0^1 (c_{it}^H)^{1-\frac{1}{\epsilon}} di\right]^{\frac{1}{1-\frac{1}{\epsilon}}}$, where each variety is indexed by i, and ϵ is the elasticity of substitution between these varieties. For any given level of demand for the composite home good c_t^H, the demand for each variety i solves the problem of minimizing total home goods expenditures, $\int_0^1 P_{it}^H c_{it}^H di$, subject to the aggregation constraint, where P_{it}^H is the nominal price of variety i. The solution to this problem yields the optimal demand for c_{it}^H, which satisfies

$$c_{it}^H = \left(\frac{P_{it}^H}{P_t^H}\right)^{-\epsilon} c_t^H,$$

with the aggregate home good price index P_t^H being

$$P_t^H = \left[\int_0^1 (P_{it}^H)^{1-\epsilon} di\right]^{\frac{1}{1-\epsilon}}.$$

Therefore, the expenditure minimization problem of households subject to the consumption aggregator (A1) produces the domestic consumer price index (CPI),

$$P_t = \left[\omega(P_t^H)^{1-\gamma} + (1-\omega)(P_t^F)^{1-\gamma}\right]^{\frac{1}{1-\gamma}}, \tag{A2}$$

and the condition that determines the optimal demand frontier for home and foreign goods,

$$\frac{c_t^H}{c_t^F} = \frac{\omega}{1-\omega}\left(\frac{P_t^H}{P_t^F}\right)^{-\gamma}. \tag{A3}$$

We assume that each household is composed of a worker and a banker who perfectly insure each other. Workers consume the consumption bundle and supply labor h_t. They also save in local currency assets which are *deposited* within financial intermediaries owned by the banker members of *other* households.[1] The balance of these deposits is denoted by B_{t+1}, which promises to pay a net nominal risk-free rate r_{nt} in the next period. There are no interbank frictions, hence r_{nt} coincides with the policy rate of the central bank. Furthermore, the borrowing contract is *real* in the sense that the risk-free rate is determined based on the expected inflation. By assumption, households cannot directly save in productive capital, and only banker members of households are able to borrow in foreign currency.

Preferences of households over consumption, leisure, and real balances are represented by the lifetime utility function

$$E_0 \sum_{t=0}^{\infty} \beta^t U\left(c_t, h_t, \frac{M_t}{P_t}\right), \tag{A4}$$

where U is a CRRA-type period utility function given by

$$U\left(c_t, h_t, \frac{M_t}{P_t}\right) = \left[\frac{(c_t - h_c c_{t-1})^{1-\sigma} - 1}{1-\sigma}\right.$$
$$\left. - \frac{\chi}{1+\xi} h_t^{1+\xi} + \upsilon \log\left(\frac{M_t}{P_t}\right)\right]. \tag{A5}$$

E_t is the mathematical expectation operator conditional on the information set available at t, $\beta \in (0,1)$ is the subjective discount rate, $\sigma > 0$ is the inverse of the intertemporal elasticity of substitution, $h_c \in [0,1)$ governs the degree of habit formation, χ is the

[1] This assumption is useful in making the agency problem that we introduce in section 3.2 more realistic.

utility weight of labor, and $\xi > 0$ determines the Frisch elasticity of labor supply. We also assume that the natural logarithm of real money balances provides utility in an additively separable fashion with the utility weight υ.[2]

Households face the flow budget constraint,

$$c_t + \frac{B_{t+1}}{P_t} + \frac{M_t}{P_t} = \frac{W_t}{P_t}h_t + \frac{(1+r_{nt-1})B_t}{P_t} + \frac{M_{t-1}}{P_t} + \Pi_t - \frac{T_t}{P_t}. \tag{A6}$$

On the right-hand side are the real wage income $\frac{W_t}{P_t}h_t$, real balances of the domestic currency interest-bearing assets at the beginning of period t $\frac{B_t}{P_t}$, and real money balances at the beginning of period t $\frac{M_{t-1}}{P_t}$. Π_t denotes real profits remitted from firms owned by the households (banks, intermediate home goods producers, and capital goods producers). T_t represents nominal lump-sum taxes collected by the government. On the left-hand side are the outlays for consumption expenditures and asset demands.

Households choose c_t, h_t, B_{t+1}, and M_t to maximize preferences in (A5) subject to (A6) and standard transversality conditions imposed on asset demands B_{t+1} and M_t. The first-order conditions of the utility maximization problem of households are given by

$$\varphi_t = (c_t - h_c c_{t-1})^{-\sigma} - \beta h_c E_t (c_{t+1} - h_c c_t)^{-\sigma}, \tag{A7}$$

$$\frac{W_t}{P_t} = \frac{\chi h_t^{\xi}}{\varphi_t}, \tag{A8}$$

$$\varphi_t = \beta E_t \left[\varphi_{t+1}(1+r_{nt}) \frac{P_t}{P_{t+1}} \right], \tag{A9}$$

$$\frac{\upsilon}{M_t/P_t} = \beta E_t \left[\varphi_{t+1} r_{nt} \frac{P_t}{P_{t+1}} \right]. \tag{A10}$$

Equation (A7) defines the Lagrange multiplier φ_t as the marginal utility of consuming an additional unit of income. Equation (A8)

[2]The logarithmic utility used for real money balances does not matter for real allocations, as it enters into the utility function in an additively separable fashion and money does not appear in any optimality condition except the consumption–money optimality condition.

equates marginal disutility of labor to the shadow value of real wages. Finally, equations (A9) and (A10) represent the Euler equations for bonds, the consumption–savings margin, and money demand, respectively.

First-order conditions (A7) and (A9) that come out of the utility maximization problem can be combined to obtain the consumption–savings optimality condition,

$$
\begin{aligned}
&(c_t - h_c c_{t-1})^{-\sigma} - \beta h_c E_t\,(c_{t+1} - h_c c_t)^{-\sigma} \\
&= \beta E_t \left[\left\{ (c_{t+1} - h_c c_t)^{-\sigma} - \beta h_c\,(c_{t+2} - h_c c_{t+1})^{-\sigma} \right\} \frac{(1 + r_{nt+1}) P_t}{P_{t+1}} \right].
\end{aligned}
$$

The consumption–money optimality condition,

$$
\frac{\upsilon / m_t}{\varphi_t} = \frac{r_{nt}}{1 + r_{nt}},
$$

on the other hand, might be derived by combining first-order conditions (A9) and (A10) with m_t denoting real balances held by consumers.

A.2 Banks' Net Worth Maximization

Bankers solve the following value maximization problem:

$$
\begin{aligned}
V_{jt} &= \max_{l_{jt+i}, b^*_{jt+1+i}} E_t \sum_{i=0}^{\infty} (1-\theta)\theta^i \Lambda_{t,t+1+i}\; n_{jt+1+i} \\
&= \max_{l_{jt+i}, b^*_{jt+1+i}} E_t \sum_{i=0}^{\infty} (1-\theta)\theta^i \Lambda_{t,t+1+i} \Big(\left[R_{kt+1+i} - \hat{R}_{t+1+i} \right] \\
&\quad \times q_{t+i} l_{jt+i} + \left[R_{t+1+i} - R^*_{t+1+i} \right] b^*_{jt+1+i} + \hat{R}_{t+1+i} n_{jt+i} \Big),
\end{aligned}
$$

subject to the constraint (7). Since

$$
V_{jt} = \max_{l_{jt+i}, b^*_{jt+1+i}} E_t \sum_{i=0}^{\infty} (1-\theta)\theta^i \Lambda_{t,t+1+i}\; n_{jt+1+i}
$$

$$= \max_{l_{jt+i}, b^*_{jt+1+i}} E_t \Bigg[(1-\theta)\Lambda_{t,t+1} n_{jt+1} + \sum_{i=1}^{\infty} (1-\theta)\theta^i \Lambda_{t,t+1+i}\, n_{jt+1+i} \Bigg],$$

we have

$$V_{jt} = \max_{l_{jt}, b^*_{jt+1}} E_t \Big\{ \Lambda_{t,t+1} [(1-\theta) n_{jt+1} + \theta V_{jt+1}] \Big\}.$$

The Lagrangian which solves the bankers' profit maximization problem reads

$$\max_{l_{jt}, b^*_{jt+1}} L = \nu_t^l q_t l_{jt} + \nu_t^* b^*_{jt+1} + \nu_t n_{jt} + \mu_t \left[\nu_t^l q_t l_{jt} + \nu_t^* b^*_{jt+1} + \nu_t n_{jt} - \lambda \left(q_t l_{jt} - \omega_l \left[\frac{q_t l_{jt} - n_{jt}}{1 - rr_t} - b^*_{jt+1} \right] \right) \right], \tag{A11}$$

where the term in square brackets represents the incentive compatibility constraint (7) combined with the balance sheet (2), to eliminate b_{jt+1}. The first-order conditions for l_{jt}, b^*_{jt+1}, and the Lagrange multiplier μ_t are

$$\nu_t^l (1 + \mu_t) = \lambda \mu_t \left(1 - \frac{\omega_l}{1 - rr_t} \right), \tag{A12}$$

$$\nu_t^* (1 + \mu_t) = \lambda \mu_t \omega_l, \tag{A13}$$

and

$$\nu_t^l q_t l_{jt} + \nu_t^* \left[\frac{q_t l_{jt} - n_{jt}}{1 - rr_t} - b_{jt+1} \right] + \nu_t n_{jt} - \lambda (q_t l_{jt} - \omega_l b_{jt+1}) \geq 0, \tag{A14}$$

respectively. We are interested in cases in which the incentive constraint of banks is always binding, which implies that $\mu_t > 0$ and (A14) holds with equality.

An upper bound for ω_l is determined by the necessary condition for a positive value of making loans $\nu_t^l > 0$, implying $\omega_l < 1 - rr_t$. Therefore, the fraction of non-diverted domestic deposits has to be smaller than one minus the reserve requirement ratio, as implied by (A12).

Combining (A12) and (A13) yields

$$\frac{\frac{\nu_t^*}{1-rr_t}}{\nu_t^l + \frac{\nu_t^*}{1-rr_t}} = \frac{\omega_l}{1 - rr_t}.$$

Rearranging the binding version of (A14) leads to equation (9).

We replace V_{jt+1} in equation (6) by imposing our linear conjecture in equation (8) and the borrowing constraint (9) to obtain

$$\tilde{V}_{jt} = E_t\Big\{\Xi_{t,t+1} n_{jt+1}\Big\}, \tag{A15}$$

where $\tilde{V}_{jt}$ stands for the optimized value.

Replacing the left-hand side to verify our linear conjecture on bankers' value (8) and using equation (5), we obtain the definition of the augmented stochastic discount factor $\Xi_{t,t+1} = \Lambda_{t,t+1}\Big[1 - \theta + \theta\Big(\zeta_{t+1}\kappa_{t+1} + \nu_{t+1} - \frac{\nu_{t+1}^*}{1-rr_{t+1}}\Big)\Big]$ and find that ν_t^l, ν_t, and ν_t^* should consecutively satisfy equations (10), (11), and (12) in the main text.

Surviving bankers' net worth n_{et+1} is derived as described in the main text and is equal to

$$\begin{aligned} n_{et+1} = \theta \Bigg(&\left[R_{kt+1} - \hat{R}_{t+1} + \frac{R_{t+1} - R_{t+1}^*}{1 - rr_t}\right]\kappa_t \\ &- \left[\frac{R_{t+1} - R_{t+1}^*}{1 - rr_t}\right] + \hat{R}_{t+1}\Bigg) n_t \\ &+ \Bigg(\left[R_{kt+1} - \hat{R}_{t+1} + \frac{R_{t+1} - R_{t+1}^*}{1 - rr_t}\right]\omega_l \\ &- \left[\frac{R_{t+1} - R_{t+1}^*}{1 - rr_t}\right]\Bigg) b_{t+1}. \end{aligned}$$

A.3 Capital Producers

Capital producers play a profound role in the model, since variations in the price of capital drives the financial accelerator. We assume that capital producers operate in a perfectly competitive market, purchase investment goods, and transform those goods into new capital. They also repair the depreciated capital that they buy from the intermediate-goods-producing firms. At the end of period t, they sell both newly produced and repaired capital to the intermediate goods firms at the unit prices of q_t and p_t^I, respectively. Intermediate goods firms use this new capital for production at time $t+1$. Capital producers are owned by households and return any earned profits to their owners. We also assume that they incur investment adjustment costs while producing new capital, given by the following quadratic function of the investment growth:

$$\Phi\left(\frac{i_t}{i_{t-1}}\right) = \frac{\Psi}{2}\left[\frac{i_t}{i_{t-1}} - 1\right]^2.$$

Capital producers use an investment good that is composed of home and foreign final goods in order to repair the depreciated capital and to produce new capital goods

$$i_t = \left[\omega_i^{\frac{1}{\gamma_i}}\left(i_t^H\right)^{\frac{\gamma_i - 1}{\gamma_i}} + (1-\omega_i)^{\frac{1}{\gamma_i}}\left(i_t^F\right)^{\frac{\gamma_i - 1}{\gamma_i}}\right]^{\frac{\gamma_i}{\gamma_i - 1}},$$

where ω_i governs the relative weight of home input in the investment composite good and γ_i measures the elasticity of substitution between home and foreign inputs. Capital producers choose the optimal mix of home and foreign inputs according to the intratemporal first-order condition

$$\frac{i_t^H}{i_t^F} = \frac{\omega_i}{1-\omega_i}\left(\frac{P_t^H}{P_t^F}\right)^{-\gamma_i}.$$

The resulting aggregate investment price index P_t^I is given by

$$P_t^I = \left[\omega_i (P_t^H)^{1-\gamma_i} + (1-\omega_i)(P_t^F)^{1-\gamma_i}\right]^{\frac{1}{1-\gamma_i}}.$$

Capital producers require i_t units of investment good at a unit price of $\frac{P_t^I}{P_t}$ and incur investment adjustment costs $\Phi\left(\frac{i_t}{i_{t-1}}\right)$ per unit of investment to produce new capital goods i_t and repair the depreciated capital, which will be sold at the price q_t. Therefore, a capital producer makes an investment decision to maximize its discounted profits represented by

$$\max_{i_{t+i}} \sum_{i=0}^{\infty} E_0 \left[\Lambda_{t,t+1+i} \left(q_{t+i} i_{t+i} - \Phi\left(\frac{i_{t+i}}{i_{t+i-1}}\right) q_{t+i} i_{t+i} - \frac{P^I_{t+i}}{P_{t+i}} i_{t+i} \right) \right]. \tag{A16}$$

The optimality condition with respect to i_t produces the following Q-investment relation for capital goods:

$$\begin{aligned} \frac{P^I_t}{P_t} = q_t &\left[1 - \Phi\left(\frac{i_t}{i_{t-1}}\right) - \Phi'\left(\frac{i_t}{i_{t-1}}\right) \frac{i_t}{i_{t-1}} \right] \\ &+ E_t \left[\Lambda_{t,t+1} q_{t+1} \Phi'\left(\frac{i_{t+1}}{i_t}\right) \left(\frac{i_{t+1}}{i_t}\right)^2 \right]. \end{aligned}$$

Finally, the aggregate physical capital stock of the economy evolves according to

$$k_{t+1} = (1-\delta_t) k_t + \left[1 - \Phi\left(\frac{i_t}{i_{t-1}}\right) \right] i_t, \tag{A17}$$

with δ_t being the endogenous depreciation rate of capital determined by the utilization choice of intermediate goods producers.

A.4 Final Goods Producers

Finished goods producers combine different varieties $y^H_t(i)$, which sell at the monopolistically determined price $P^H_t(i)$, into a final good that sells at the competitive price P^H_t, according to the constant-returns-to-scale technology,

$$y^H_t = \left[\int_0^1 y^H_t(i)^{1-\frac{1}{\epsilon}} di \right]^{\frac{1}{1-\frac{1}{\epsilon}}}.$$

The profit maximization problem of final goods producers is represented by

$$\max_{y^H_t(i)} \; P^H_t \left[\int_0^1 y^H_t(i)^{1-\frac{1}{\epsilon}} di \right]^{\frac{1}{1-\frac{1}{\epsilon}}} - \left[\int_0^1 P^H_t(i) y^H_t(i) di \right]. \tag{A18}$$

The profit maximization problem, combined with the zero profit condition, implies that the optimal variety demand is

$$y_t^H(i) = \left(\frac{P_t^H(i)}{P_t^H}\right)^{-\epsilon} y_t^H,$$

with $P_t^H(i)$ and P_t^H satisfying

$$P_t^H = \left[\int_0^1 P_t^H(i)^{1-\epsilon} di\right]^{\frac{1}{1-\epsilon}}.$$

We assume that imported intermediate good varieties are repackaged via a similar technology with the same elasticity of substitution between varieties as in domestic final good production. Therefore, $y_t^F(i) = \left(\frac{P_t^F(i)}{P_t^F}\right)^{-\epsilon} y_t^F$ and $P_t^F = \left[\int_0^1 P_t^F(i)^{1-\epsilon} di\right]^{\frac{1}{1-\epsilon}}$ hold for imported intermediate goods.

A.5 Intermediate Goods Producers

There is a large number of intermediate goods producers, indexed by i, who produce variety $y_t^H(i)$ using the constant-returns-to-scale production technology,

$$y_t^H(i) = A_t\Big(u_t(i)k_t(i)\Big)^{\alpha} h_t(i)^{1-\alpha}.$$

As shown in the production function, firms choose the level of capital and labor used in production, as well as the utilization rate of the capital stock. A_t represents the aggregate productivity level and follows an autoregressive process given by

$$\ln(A_{t+1}) = \rho^A \ln(A_t) + \epsilon_{t+1}^A,$$

with zero mean and constant variance innovations ϵ_{t+1}^A.

Part of $y_t(i)$ is sold in the domestic market as $y_t^H(i)$, in which the producer i operates as a monopolistically competitor. Accordingly, the nominal sales price $P_t^H(i)$ is chosen by the firm to meet the aggregate domestic demand for its variety,

$$y_t^H(i) = \left(\frac{P_t^H(i)}{P_t^H}\right)^{-\epsilon} y_t^H,$$

which depends on the aggregate home output y_t^H. Apart from incurring nominal marginal costs of production MC_t, these firms additionally face Rotemberg (1982)-type quadratic menu costs of price adjustment in the form of

$$P_t \frac{\varphi^H}{2} \left[\frac{P_t^H(i)}{P_{t-1}^H(i)} - 1 \right]^2 .$$

These costs are denoted in nominal terms, with φ^H capturing the intensity of the price rigidity.

Domestic intermediate goods producers choose their nominal price level to maximize the present discounted real profits. We confine our interest to symmetric equilibrium, in which all intermediate producers choose the same price level, that is, $P_t^H(i) = P_t^H \ \forall i$.

Domestic intermediate goods producers' profit maximization problem can be represented as follows:

$$\max_{P_t^H(i)} E_t \sum_{j=0}^{\infty} \Lambda_{t,t+j} \left[\frac{D_{t+j}^H(i)}{P_{t+j}} \right] \tag{A19}$$

subject to the nominal profit function

$$\begin{aligned} D_{t+j}^H(i) &= P_{t+j}^H(i) y_{t+j}^H(i) + S_{t+j} P_{t+j}^{H*} c_{t+j}^{H*}(i) - MC_{t+j} y_{t+j}^H(i) \\ &\quad - P_{t+j} \frac{\varphi^H}{2} \left[\frac{P_{t+j}^H(i)}{P_{t+j-1}^H(i)} - 1 \right]^2 \end{aligned} \tag{A20}$$

and the demand function $y_t^H(i) = \left(\frac{P_t^H(i)}{P_t^H} \right)^{-\epsilon} y_t^H$. Since households own these firms, any profits are remitted to consumers and future streams of real profits are discounted by the stochastic discount factor of consumers, accordingly. Notice that the sequences of the nominal exchange rate and export prices in foreign currency $\{S_{t+j}, P_{t+j}^{H*}\}_{j=0}^{\infty}$ are taken exogenously by the firm, since it acts as a price taker in the export market. The first-order condition to this problem becomes

$$
\begin{aligned}
(\epsilon - 1)\left(\frac{P_t^H(i)}{P_t^H}\right)^{-\epsilon}\frac{y_t^H}{P_t} = \epsilon &\left(\frac{P_t^H(i)}{P_t^H}\right)^{-\epsilon-1} MC_t\frac{y_t^H}{P_tP_t^H} \\
&- \varphi^H\left[\frac{P_t^H(i)}{P_{t-1}^H(i)} - 1\right]\frac{1}{P_{t-1}^H(i)} \\
&+ \varphi^H E_t\left\{\Lambda_{t,t+1}\left[\frac{P_{t+1}^H(i)}{P_t^H(i)} - 1\right]\frac{P_{t+1}^H(i)}{P_t^H(i)^2}\right\}.
\end{aligned} \tag{A21}
$$

Imposing the symmetric equilibrium condition to the first-order condition of the profit maximization problem and using the definitions $rmc_t = \frac{MC_t}{P_t}$, $\pi_t^H = \frac{P_t^H}{P_{t-1}^H}$, and $p_t^H = \frac{P_t^H}{P_t}$ yields

$$
\begin{aligned}
p_t^H = \frac{\epsilon}{\epsilon - 1} rmc_t &- \frac{\varphi^H}{\epsilon - 1}\frac{\pi_t^H(\pi_t^H - 1)}{y_t^H} \\
&+ \frac{\varphi^H}{\epsilon - 1}E_t\left\{\Lambda_{t,t+1}\frac{\pi_{t+1}^H(\pi_{t+1}^H - 1)}{y_t^H}\right\}.
\end{aligned} \tag{A22}
$$

Notice that even if prices are flexible—that is, $\varphi^H = 0$—the monopolistic nature of the intermediate goods market implies that the optimal sales price reflects a markup over the marginal cost, that is, $P_t^H = \frac{\epsilon}{\epsilon-1}MC_t$.

The remaining part of the intermediate goods is exported as $c_t^{H*}(i)$ in the foreign market, where the producer is a price taker. To capture the foreign demand, we follow Gertler, Gilchrist, and Natalucci (2007) and impose an autoregressive exogenous export demand function in the form of

$$
c_t^{H*} = \left[\left(\frac{P_t^{H*}}{P_t^*}\right)^{-\Gamma} y_t^*\right]^{\nu^H}(c_{t-1}^{H*})^{1-\nu^H},
$$

which positively depends on foreign output that follows an autoregressive exogenous process,

$$
\ln(y_{t+1}^*) = \rho^{y^*}\ln(y_t^*) + \epsilon_{t+1}^{y^*},
$$

with zero mean and constant variance innovations. The innovations to the foreign output process are perceived as export demand shocks by the domestic economy. For tractability, we further assume that the small open economy takes $P_t^{H*} = P_t^* = 1$ as given. We think that this model feature is realistic for Turkey and other emerging market economies in general considering the observed export structure of these economies.

Imported intermediate goods are purchased by a continuum of producers that are analogous to the domestic producers except that these firms face exogenous import prices as their marginal cost. In other words, the law of one price holds for the import prices, so that $MC_t^F = S_t P_t^{F*}$. Since these firms also face quadratic price adjustment costs, the domestic price of imported intermediate goods is determined as

$$p_t^F = \frac{\epsilon}{\epsilon - 1} s_t - \frac{\varphi^F}{\epsilon - 1} \frac{\pi_t^F(\pi_t^F - 1)}{y_t^F} + \frac{\varphi^F}{\epsilon - 1} E_t \left\{ \Lambda_{t,t+1} \frac{\pi_{t+1}^F(\pi_{t+1}^F - 1)}{y_t^F} \right\}, \tag{A23}$$

with $p_t^F = \frac{P_t^F}{P_t}$, $s_t = \frac{S_t P_t^{F*}}{P_t}$, and $P_t^{F*} = 1\ \forall t$ is taken exogenously by the small open economy.

For a given sales price, optimal factor demands and utilization of capital are determined by the solution to a symmetric cost minimization problem, where the cost function shall reflect the capital gains from market valuation of firm capital and resources that are devoted to the repair of the worn-out part of it. Consequently, firms minimize

$$\begin{aligned} \min_{u_t, k_t, h_t} \; & q_{t-1} r_{kt} k_t - (q_t - q_{t-1}) k_t + p_t^I \delta(u_t) k_t + w_t h_t \\ & + rmc_t \left[y_t^H - A_t \Big(u_t k_t \Big)^{\alpha} h_t^{1-\alpha} \right] \end{aligned} \tag{A24}$$

subject to the endogenous depreciation rate function,

$$\delta(u_t) = \delta + \frac{d}{1 + \varrho} u_t^{1+\varrho}, \tag{A25}$$

with $\delta, d, \varrho > 0$. The first-order conditions to this problem govern factor demands and the optimal utilization choice as

$$p_t^I \delta'(u_t) k_t = \alpha \left(\frac{y_t^H}{u_t} \right) rmc_t, \tag{A26}$$

$$R_{kt} = \frac{\alpha\left(\frac{y_t^H}{k_t}\right) rmc_t - p_t^I \delta(u_t) + q_t}{q_{t-1}}, \tag{A27}$$

and

$$w_t = (1-\alpha)\left(\frac{y_t^H}{h_t}\right) rmc_t. \tag{A28}$$

A.6 Resource Constraints

The resource constraint for home goods equates domestic production to the sum of domestic and external demand for home goods and the real domestic price adjustment costs, so that

$$y_t^H = c_t^H + c_t^{H*} + i_t^H + g_t^H y_t^H + \left(p_t^H\right)^{-\gamma} \frac{\varphi^H}{2}\left(\pi_t \frac{p_t^H}{p_{t-1}^H} - 1\right)^2. \tag{A29}$$

A similar market clearing condition holds for the domestic consumption of the imported goods, that is,

$$y_t^F = c_t^F + i_t^F + \left(p_t^F\right)^{-\gamma} \frac{\varphi^F}{2}\left(\pi_t \frac{p_t^F}{p_{t-1}^F} - 1\right)^2. \tag{A30}$$

Finally, the balance of payments vis-à-vis the rest of the world defines the trade balance as a function of net foreign assets,

$$R_t^* b_t^* - b_{t+1}^* = c_t^{H*} - y_t^F. \tag{A31}$$

A.7 Definition of Competitive Equilibrium

A competitive equilibrium is defined by sequences of prices $\left\{p_t^H, p_t^F, p_t^I, \pi_t, w_t, q_t, s_t, R_{kt+1}, R_{t+1}, R_{t+1}^*\right\}_{t=0}^{\infty}$; government policies $\{r_{nt}, rr_t, M_{0t}, T_t\}_{t=0}^{\infty}$; allocations $\left\{c_t^H, c_t^F, c_t, h_t, m_t, b_{t+1}, b_{t+1}^*, \varphi_t, l_t, n_t, \kappa_t, \nu_t^l, \nu_t^*, \nu_t, i_t, i_t^H, i_t^F, k_{t+1}, y_t^H, y_t^F, u_t, rmc_t, c_t^{H*}, D_t^H, \Pi_t, \delta_t\right\}_{t=0}^{\infty}$; initial conditions $b_0, b_0^*, k_0, m_-, n_0$; and exogenous processes $\left\{A_t, g_t^H, \psi_t, r_{nt}^*, y_t^*\right\}_{t=0}^{\infty}$ such that

(i) Given exogenous processes, initial conditions, government policy, and prices, the allocations solve the utility maximization problem of households (A5)–(A6); the net worth maximization problem of bankers (6)–(7); and the profit maximization problems of capital producers (A16), final goods producers (A18), and intermediate goods producers (A19)–(A20) and (A24)–(A25).

(ii) Home and foreign goods, physical capital, investment, security claims, domestic deposits, money, and labor markets clear. The balance of payments identity (A31) holds.

Appendix B. Impulse Responses under Domestic and Other External Shocks

Figures B1–B4 in this section present the impulse responses of real, financial, and external variables under the productivity, government spending, U.S. policy rate, and export demand shocks. For brevity, we do not explain the dynamics of model variables under each shock in detail. We note that most of the endogenous variables and the policy instruments respond to each shock in a fairly standard way, which was already extensively studied in the previous literature. In this section, we also report one-quarter-ahead and one-year-ahead variance decomposition results (see table B1 below), which were not reported in the main text.

Table B1. Variance Decomposition in the Decentralized Economy (%)

One Quarter Ahead	TFP	Gov't. Spending	Country Risk Premium	U.S. Interest Rate	Export Demand
Output	16.41	67.89	13.05	2.38	0.27
Consumption	17.69	0.12	69.81	12.36	0.03
Investment	5.11	0.00	80.86	13.98	0.05
Credit	96.45	2.54	0.77	0.12	0.11
Liability Composition (Foreign)	1.64	0.01	83.97	14.32	0.05
Loan–Domestic Deposit Spread	0.04	0.00	84.50	15.36	0.10
Loan–Foreign Deposit Spread	0.75	0.00	84.70	14.49	0.05
Real Exchange Rate	1.12	0.01	86.41	12.45	0.01
CA Balance to GDP	0.04	0.00	79.93	13.72	6.31
Trade Balance to GDP	0.18	0.25	79.87	13.73	5.98
Inflation Rate	36.25	0.21	56.00	7.55	0.00
Policy Rate	36.25	0.21	56.00	7.55	0.00
One Year Ahead					
Output	37.33	15.59	39.67	7.14	0.27
Consumption	15.98	0.10	71.23	12.66	0.03
Investment	6.17	0.00	79.89	13.90	0.05
Credit	70.40	1.40	23.71	4.19	0.31
Liability Composition (Foreign)	9.34	0.08	77.57	12.98	0.04
Loan–Domestic Deposit Spread	0.91	0.00	84.48	14.58	0.03
Loan–Foreign Deposit Spread	0.28	0.02	85.06	14.61	0.02
Real Exchange Rate	1.90	0.02	85.50	12.56	0.02
CA Balance to GDP	1.30	0.02	84.33	14.17	0.18
Trade Balance to GDP	0.94	0.02	83.12	14.46	1.45
Inflation Rate	27.13	0.14	64.14	8.60	0.00
Policy Rate	23.32	0.09	67.55	9.05	0.00

Figure B1. Impulse Response Functions Driven by a One-Standard-Deviation Increase in Productivity

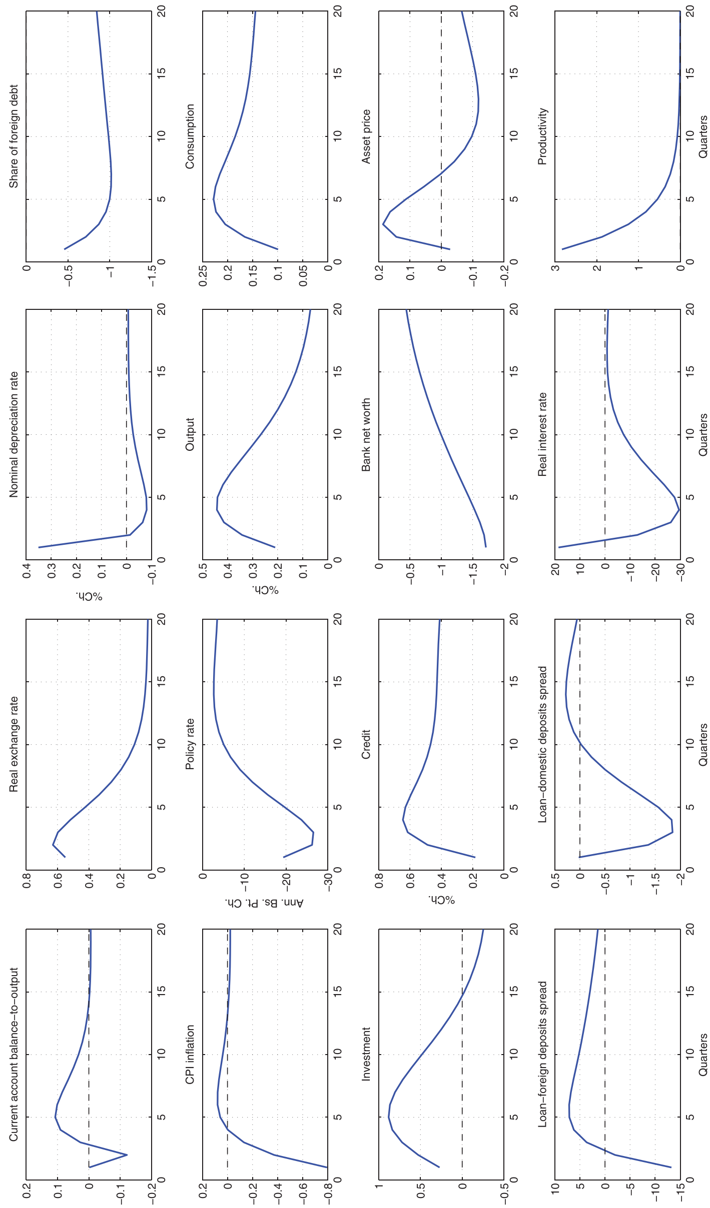


Figure B2. Impulse Response Functions Driven by a One-Standard-Deviation Increase in Government Spending

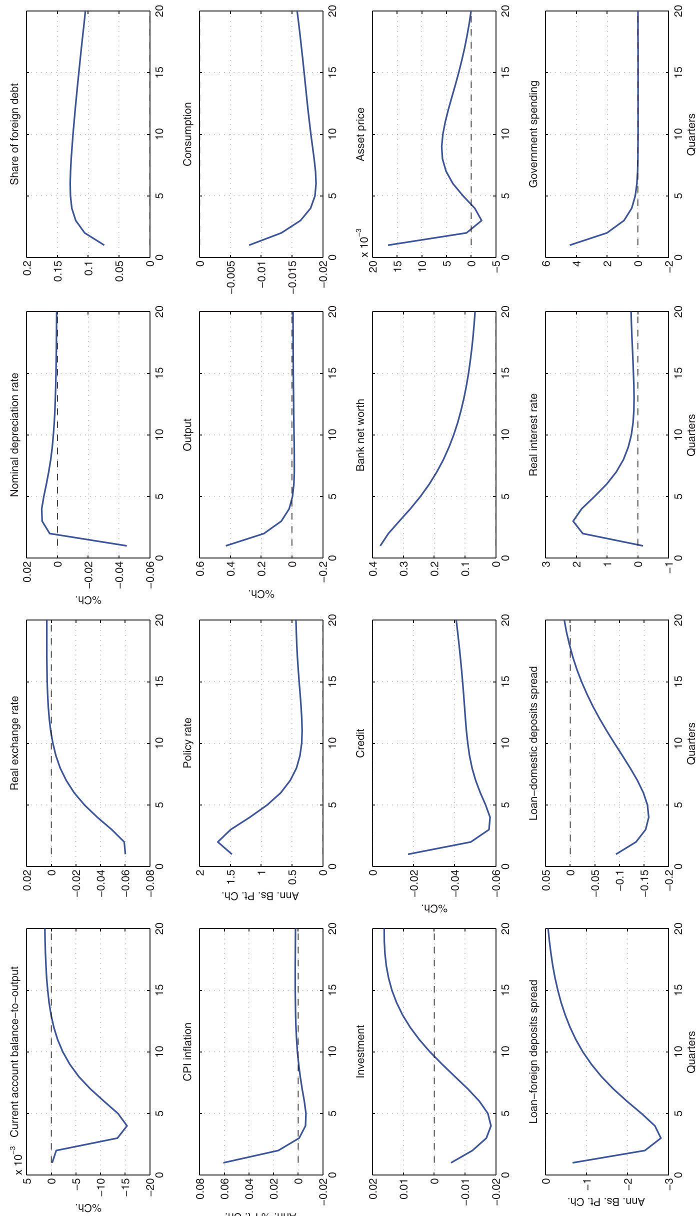


Figure B3. Impulse Response Functions Driven by a 40 Annualized Basis Point Increase in the U.S. Policy Rate

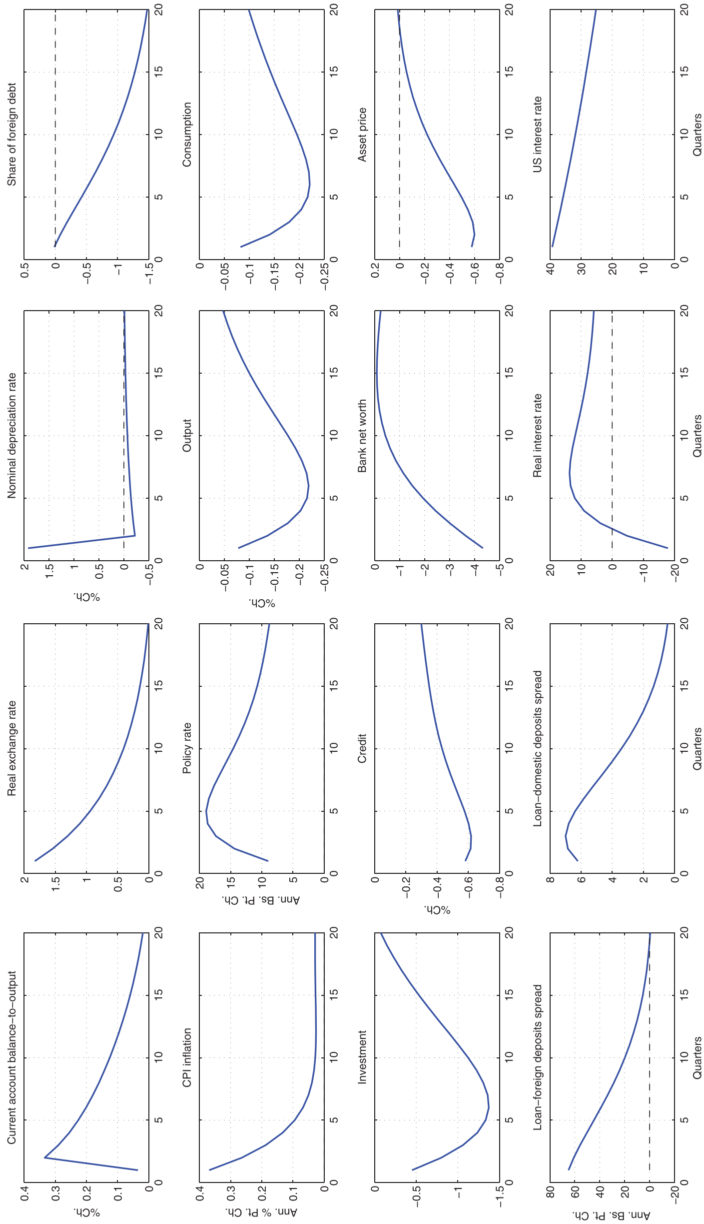
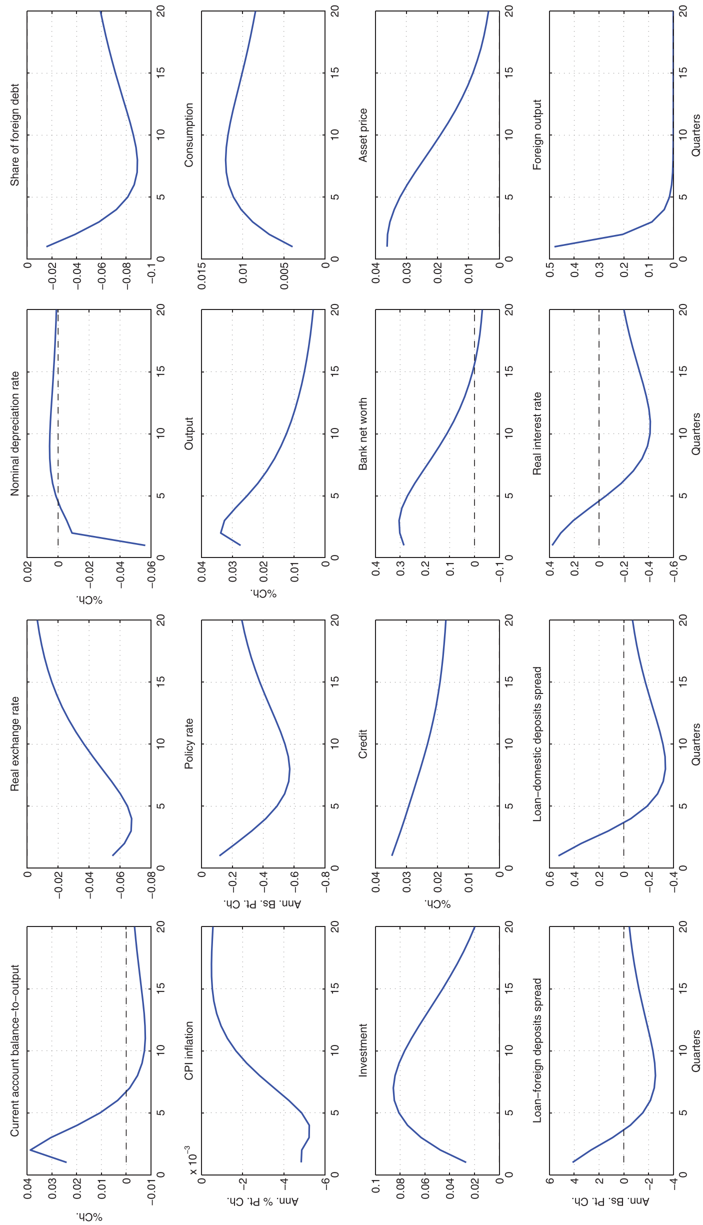


Figure B4. Impulse Response Functions Driven by a One-Standard-Deviation Increase in Foreign Output



Appendix C. Optimal Simple Rules under Domestic Shocks

Table C1 reports the response coefficients of optimized conventional and augmented Taylor rules, the absolute volatilities of policy rate, inflation, lending spread over foreign debt and the real exchange rate (RER) under these rules, and the corresponding consumption-equivalent welfare costs relative to the Ramsey-optimal policy under productivity and government spending shocks.

The optimized Taylor rules with and without smoothing feature no response to output variations under productivity shocks, which is consistent with the results of Schmitt-Grohé and Uribe (2007) in a canonical closed-economy New Keynesian model without credit frictions. The optimal simple rule with smoothing displays a large degree of inertia and a limited response to the CPI inflation. The latter result is in line with Schmitt-Grohé and Uribe (2007) in the sense that the level of the response coefficient of inflation plays a limited role for welfare and it matters to the extent that it affects the determinacy. It is also in line with Monacelli (2005, 2013) and Faia and Monacelli (2008), since open-economy features such as home bias and incomplete exchange rate pass-through may cause the policymaker to deviate from strict domestic markup stabilization and resort to some degree of exchange rate stabilization. Higher volatilities of inflation and credit spreads together with a lower volatility of asset prices compared with the Ramsey policy indicate that these two optimized Taylor rules can only partially stabilize the intratemporal and intertemporal wedges, explaining the welfare losses associated with these rules.

Under productivity shocks, optimized augmented Taylor rules suggest that a negative response to credit spreads together with a moderate response to inflation and a strong response to output deviations achieve the highest welfare possible. In response to a 100 basis points increase in credit spreads, the policy should be reduced by 150 basis points, all else equal. This policy substantially reduces the volatility of spreads in comparison with that in the Ramsey policy. Moreover, the optimized augmented Taylor rules that respond to credit, asset prices, or the real exchange rate also achieve a level of welfare very close to that implied by the spread-augmented Taylor rule. Both rules feature a lower degree of volatility of the real

Table C1. Optimal Simple Policy Rules under Domestic Shocks

TFP	ρ_{r_n}	φ_π	φ_y	φ_f	ρ_{rr}	φ_{rr}	σ_{r_n}	σ_π	σ_{spread}	σ_{RER}	σ_q	**CEV(%)**[a]
Optimized Taylor Rules (TR)												
Standard (without smoothing)	–	1.5721	0	–	–	–	0.2701	0.3071	0.0830	0.4714	0.4155	2.2690
Standard (with smoothing)	0.9950	1.0010	0	–	–	–	0.0015	0.2559	0.1183	0.9274	0.6568	1.3583
Optimized Augmented TR												
Credit	0.7818	1.2866	2.7857	−1.7143	–	–	0.4441	0.4697	0.1008	1.1231	1.0792	0.0010
Asset Price	0.4264	3.0000	2.7857	−3.0000	–	–	2.9289	0.7777	0.4339	4.5204	3.5392	0.0009
Credit Spread	0.9239	1.2866	1.2857	−1.5000	–	–	0.2268	0.3903	0.0234	1.3792	0.4942	0.0001
Real Exchange Rate	0.7107	1.0010	1.9286	2.7857	–	–	0.3718	0.4431	0.8391	1.1026	5.2674	0.0014
Optimized TR and RRR	0.1421	2.8572	1.0714	–	0.7107	−2.7857	0.4204	0.5282	14.5650	12.8479	4.3218	0.0008
Ramsey Policy	–	–	–	–	–	–	0.2248	0.1703	0.0623	1.5168	1.1261	0
Gov't. Spending	ρ_{r_n}	φ_π	φ_y	φ_f	ρ_{rr}	φ_{rr}	σ_{r_n}	σ_π	σ_{spread}	σ_{RER}	σ_q	**CEV(%)**[a]
Optimized Taylor Rules (TR)												
Standard (without smoothing)	–	1.0010	0.2143	–	–	–	0.0725	0.0427	0.0290	0.1186	0.1641	2.0672
Standard (with smoothing)	0.9950	1.0010	0.4286	–	–	–	0.0009	0.0145	0.0064	0.0949	0.0616	2.0106
Optimized Augmented TR												
Credit	0.9950	1.1438	1.5000	−0.8571	–	–	0.0089	0.2327	0.2649	0.4117	1.7141	0.0332
Asset Price	0.9950	2.4289	1.2857	−2.3571	–	–	0.0278	0.1991	0.2551	0.4078	1.6741	0.0010
Credit Spread	0.3554	1.2866	0.2143	−2.5714	–	–	0.3014	0.4829	0.0007	0.6864	0.2662	0.0147
Real Exchange Rate	0.1421	1.2866	2.3571	−2.7857	–	–	0.3445	0.3008	0.4325	1.2370	3.3088	0.0005
Optimized TR and RRR	0.9950	1.1438	0.8571	–	0.2843	−3.0000	0.0040	0.1182	0.0521	0.2786	0.8837	0.0001
Ramsey Policy	–	–	–	–	–	–	0.0144	0.0146	0.0060	0.0961	0.0508	0

[a]The reported welfare figures include both long-run and dynamic costs.

exchange rate in comparison with that in the Ramsey policy. We also observe that it is optimal to negatively respond to bank credit under productivity shocks. In addition, comparing volatilities of key variables under these augmented Taylor rules displays the nature of the policy tradeoffs that the central bank faces. For instance, although the spread-augmented rule features a lower volatility of the credit spreads relative to the Ramsey policy as can be expected, it displays a much higher volatility in the CPI inflation rate. In addition, the optimized RER-augmented rule features a lower volatility in the real exchange rate as expected, but it displays much larger variations in the inflation rate and the credit spread against the Ramsey-optimal policy.

Optimized augmented Taylor rules under the government spending shock suggest similar results in general when compared to those under the TFP shock, except the following. In response to this domestic demand shock which pushes inflation and output in the same direction, the optimized standard Taylor rules with and without smoothing display a positive response to output. Moreover, the best policy is to respond to the RER instead of credit spreads in the case of the TFP shock.

References

Faia, E., and T. Monacelli. 2008. "Optimal Monetary Policy in a Small Open Economy with Home Bias." *Journal of Money, Credit and Banking* 40 (4): 721–50.

Galí, J., and T. Monacelli. 2005. "Monetary Policy and Exchange Rate Volatility in a Small Open Economy." *Review of Economic Studies* 72 (3): 707–34.

Gertler, M., S. Gilchrist, and F. Natalucci. 2007. "External Constraints on Monetary Policy and the Financial Accelerator." *Journal of Money, Credit and Banking* 39 (2/3): 295–330.

Monacelli, T. 2005. "Monetary Policy in a Low Pass-Through Environment." *Journal of Money, Credit and Banking* 37 (6): 1047–66.

———. 2013. "Is Monetary Policy in an Open Economy Fundamentally Different?" *IMF Economic Review* 61 (1): 6–21.

Rotemberg, J. J. 1982. "Sticky Prices in the United States." *Journal of Political Economy* 90 (6): 1187–1211.

Schmitt-Grohé, S., and M. Uribe. 2007. "Optimal Simple and Implementable Monetary and Fiscal Rules." *Journal of Monetary Economics* 54 (6): 1702–25.

International Monetary Policy Coordination through Communication: Chasing the Loch Ness Monster*

Serkan Imisiker[a] and Bedri Kamil Onur Tas[b]
[a]Independent Researcher
[b]TOBB University of Economics and Technology

We empirically examine international monetary policy coordination. We use the Global Economy Meetings (GEMs) at the Bank for International Settlements (BIS) to design a novel empirical identification strategy. We find that communication between the central bank governors at the BIS GEMs promotes policy coordination.

JEL Codes: E52, E58.

1. Introduction

International monetary coordination has become a major policy argument since the global financial crisis. However, there is little evidence of coordination among central banks. Blanchard, Ostry, and Gosh (2013) even call policy coordination "the Loch Ness monster: much discussed but rarely seen." In this paper, we chase the Loch Ness monster and empirically examine the existence of international monetary policy coordination.

Although various studies report significant spillover from the Federal Reserve's monetary policy actions to its counterparts (e.g., Edwards 2015 and Hofmann and Takáts 2015), empirical evidence about the existence of monetary coordination does not exist in the

*We would like to thank Kaushik Jayaram, Michalis Ghalanos, and an anonymous referee for extremely helpful comments. Corresponding author (Onur Tas): TOBB University of Economics and Technology, Department of Economics, Sogutozu Cad. No. 43, 06530 Sogutozu, Ankara, Turkey. E-mail: onurtas@etu.edu.tr.

literature. In this paper, we use the Bank for International Settlements (BIS) meetings to identify coordination empirically. We investigate whether the increased means of communication between governors of central banks have any effect on the correlation of monetary policy decisions.

Borio and Toniolo (2006) classify central bank cooperation in two categories. "Low-key" cooperation expresses the exchange of information between central banks, whereas "high-profile" cooperation is about joint actions. Throughout the history of central banking, the former type of cooperation becomes evident, especially after the establishment of the BIS. The latter is mostly seen in the wake of large-scale financial turbulences.[1] Bernanke (2014) mentions the importance of the BIS meetings. He states that "the Fed Chairman or Vice Chairman meets with emerging market governors at least eight to ten times a year, for an hour or more, at the BIS and other contacts, to explain policy and to hear comments. So, there's an awful lot of consultation."

The BIS is the foremost venue for central bank cooperation. It is a crucial ground for central bankers to share their experiences on common problems. The BIS, regarded as a genuine meeting point of central bankers from its sixty members, organizes regular meetings for the high-level representatives of central banks. Among these gatherings, the bimonthly Global Economy Meeting (GEM) that brings together the governors of major monetary authorities is one of the significant events. Former President of the European Central Bank Jean-Claude Trichet emphasizes the importance of GEMs as the following:[2]

> In the area of central bank cooperation, the main forum is the Global Economy Meeting (GEM) ... The GEM, in which all systemic emerging economies' Central Bank governors are fully participating, has become the prime group for global governance

---

[1] Joint actions of the central banks of Bank of Canada, the Bank of England, the European Central Bank, the Federal Reserve, Sveriges Riksbank, and the Swiss National Bank on October 8, 2008 can be given as an example of "high-profile" cooperation of central banks.

[2] Jean-Claude Trichet, "Global Governance Today" (keynote address, Council on Foreign Relations, New York, April 26, 2010). Available at http://www.bis.org/review/r100428b.pdf.

> among central banks. The GEM has become a very important forum for assessing global economic and financial conditions, for analyzing economic and financial policy issues of common interest to central banks. ... I find the candid exchange of views of our bi-monthly meetings of enormous value.

Following these arguments, we conduct several empirical analyses to investigate whether monetary policy decisions of the central banks where the governor participates in the GEM are more synchronized than those of outsiders. Using different econometric specifications, we find that GEM participants have significantly higher correlation of monetary policy actions, a sign of greater coordination.

2. Data and Methodology

Starting with the 2009 Annual Report, the BIS announces the list of countries from which the central bank governors participate in the GEM.[3] There are two categories for the participant countries, namely members and observers. Governors from thirty-one central banks attend the meeting as members of the GEM. The number of observer central banks is seventeen until 2012 and nineteen afterwards. Central banks of Colombia and Peru are the latecomers to the observer list. We collect the list of the countries by reading the BIS Annual Reports. We consider both the attendants and observers as GEM participants since all the governors are present at the meetings and have full access to the means of communication at the GEM.[4] We eliminate the countries with currency board and

[3]As stated by the 2014 BIS Annual Report, "The members of the GEM are the central bank Governors of Argentina, Australia, Belgium, Brazil, Canada, China, France, Germany, Hong Kong SAR, India, Indonesia, Italy, Japan, Korea, Malaysia, Mexico, the Netherlands, Poland, Russia, Saudi Arabia, Singapore, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, the United Kingdom, and the United States and also the President of the European Central Bank and the President of the Federal Reserve Bank of New York. The Governors attending as observers are from Algeria, Austria, Chile, Colombia, the Czech Republic, Denmark, Finland, Greece, Hungary, Ireland, Israel, Luxembourg, New Zealand, Norway, Peru, the Philippines, Portugal, Romania, and the United Arab Emirates."

[4]We also conduct the regression analysis using separate variables for attendants and observers. The results are not affected by this alternative specification. The alternative estimation results are available from the authors upon request.

conventional peg exchange rate regimes as listed in the "Annual Report on Exchange Arrangements and Exchange Restrictions" (AREAER) of the International Monetary Fund (IMF).[5] After removing the national central banks in the euro zone,[6] we have fifty-three central banks in our data set that includes twenty-one members and eight observers (ten after 2012) of the GEM.[7] We display the list of countries in table 7 in the appendix.

We measure the cross-country coherences of monetary policy by computing the Pearson's correlation coefficients (PCCs) of the cyclical components of the money market rate.[8] We follow Aizenman, Chinn, and Ito (2008) and employ money market rates extracted from the IMF International Financial Statistics (IFS) database to assess monetary policy. We calculate the cyclical components using the Hodrick-Prescott filter following Vegh and Vuletin (2012). Studies like Flood and Rose (2010) use the PCC to assess the time-varying relationship between cyclical components of macroeconomic variables.

We calculate the PCCs using twenty-four monthly observations using the following specification:

$$\rho_{a,b,\tau} = \frac{1}{T-1} \sum_{t=1}^{\tau} \left(\frac{i^d_{a,t} - i^d_{a,\tau}}{i^d_{a,\tau}} \right) \left(\frac{i^d_{b,t} - i^d_{b,\tau}}{i^d_{b,\tau}} \right). \qquad (1)$$

$\rho_{a,b,\tau}$ is the sample correlation coefficient estimated between the cyclical components of money market rates (i) for countries a and

[5] The AREAERs are available at http://www.elibrary-areaer.imf.org/Pages/Home.aspx. The most notable central banks that we drop are Bahrain, Bulgaria, Denmark, Hong Kong SAR, Jordan, Morocco, Oman, Qatar, Saudi Arabia, United Arab Emirates, and Venezuela, among others. We have conducted the empirical analysis using an extended data set of seventy-one central banks. We obtain similar results. The results with the extended data set are available from the authors upon request.

[6] Belgium, France, Germany, Italy, the Netherlands, and Spain are GEM attendants that are European Economic and Monetary Union (EMU) countries. Austria, Finland, Greece, Ireland, Luxembourg, and Portugal are EMU countries that are GEM observers. Latvia became a member of the EMU on January 1, 2014. Before adopting the euro, Latvia implemented a conventional peg exchange rate regime.

[7] Money market rate is missing for Algeria and China for certain months.

[8] We employ the central bank average funding rate for the Central Bank of Turkey as suggested by Kara (2015).

b over the twenty-four (T) months preceding through time τ. We compute this statistic between pairs of countries over time and use it as the key measure of monetary policy coordination. This measure allows us to assess the time-varying structure of monetary policy synchronization. We calculate the PCCs of country pairs for April 2009–September 2014. We use the cyclical components of money market rates since interest rates of developed countries share a common trend which might superficially increase the PCCs. We conduct several robustness analyses by employing alternative measures of changes in monetary policy in section 4.

Figure 1 displays the histogram of the PCC among different country pairs.

We estimate the following regression specification of Flood and Rose (2010) to examine the impact of increased means of communication at the BIS meetings on monetary policy co-movement:

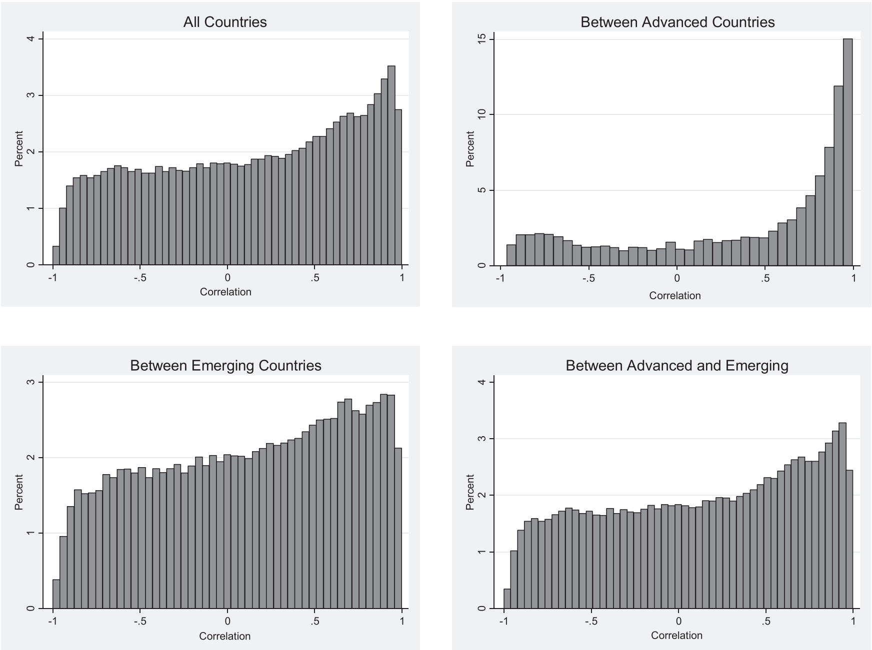
$$\begin{aligned}\rho_{a,b,\tau} = {} & \beta_0 + \beta_1 Both\ BIS_{a,b,\tau} + \beta_2 Both\ Advanced_{a,b,\tau} \\ & + B\theta_\tau + \varepsilon_{a,b,\tau}.\end{aligned} \tag{2}$$

Both BIS is a dummy variable that is unity if both countries a and b attend the BIS GEM meetings; *Both Advanced* is a dummy variable for correlation between advanced countries; θ_τ contains the time-varying control variables that are the cyclical component of the shadow policy rate of the Federal Reserve (Wu and Xia 2016), the VIX index, the minimum of the financial openness index of countries a and b,[9] and a measure of business cycle synchronization. We gauge business cycle synchronization of countries a and b by calculating PCCs of cyclical components of real GDP of country pairs, $\rho^{bc}_{a,b,\tau}$, as in Flood and Rose (2010). The business cycle synchronization measure, $\rho^{bc}_{a,b,\tau}$, is the sample correlation coefficient estimated between the cyclical components of real GDP for countries a and b over the twenty-four (T) months preceding through time τ as described in equation (1).

The VIX index contains essential information about global capital flows. Rey (2015, p. 1) finds that "there is a global financial

[9] We employ the index produced by Chinn and Ito (2006). The index is available for years 1970–2014 for 182 countries.

Figure 1. Histogram of the Time-Varying Correlation Measure



cycle in capital flows, assets prices and in credit growth." She concludes that the VIX is closely related to the global capital flows. Therefore, we control for global capital flows that might significantly affect interest rates by employing the VIX index as a control variable. Furthermore, VAR analysis conducted by Rey (2015) concludes that U.S. monetary policy is one of the major determinants of the global financial cycle. Accordingly, we use the shadow policy rate of the Fed to control for the changes in the U.S. monetary policy. We estimate equation (2) using the random-effects estimator with Huber-White robust standard errors. We also employ month fixed effects.

Additionally, we consider that membership to the GEM might be endogenous. We employ an instrumental-variable (IV) estimation approach. We instrument for the *Both* $BIS_{a,b,\tau}$ variable and estimate the coefficients of equation (2) using an IV GMM methodology.

We implement the heteroskedasticity-based instrumental-variable (HB-IV) methodology developed by Lewbel (2012). The methodology provides an unbiased and consistent estimate of the parameters when the regression model contains endogenous or mismeasured regressors, or when the model suffers from the omitted-variable bias. Monte Carlo study results and numerous empirical applications presented in Lewbel (2012) show that the estimator works well compared with two-stage least squares and GMM when valid instrumental variables are not available.[10] The methodology of Lewbel (2012) uses the heteroskedasticity of the errors to achieve identification through observing a vector of regressor variables uncorrelated with the covariance of heteroskedastic errors.

We use HB-IV since it does not require predetermined instrumental variables to produce unbiased and consistent estimates of the parameters. We do not determine the instrumental variables in the HB-IV methodology. Instead, the method builds valid IVs (uncorrelated with the error term) using the heteroskedasticity structure of the error terms and employs these valid IVs to conduct IV GMM estimation. Accordingly, HB-IV allows us to examine the soundness of the panel estimation results.

3. Empirical Analysis

We gauge the existence and level of coordination among central banks by estimating the impact of means of communication at the BIS meetings on time-varying correlation of cyclical components of monetary policy actions of fifty-three central banks. Table 1 shows the coefficients of equation (2) estimated using both random-effects panel regression and HB-IV GMM. The coefficient of the *Both BIS* dummy variable, β_1, measures the impact of communication at the BIS GEM.

The coefficient of the *Both BIS* dummy variable is significant, with a positive coefficient indicating that central banks that

[10] Lewbel (2012, p. 77) states that "the proposed estimators appear to work well in both a small Monte Carlo study ... and in an empirical application. Citing working paper versions of the present article, some articles by other researchers listed earlier include empirical applications of the proposed estimators and find them to work well in practice."

Table 1. Effect of Communication at the BIS Meetings on International Monetary Policy Coordination

	Random-Effects Panel				HB-IV GMM			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Both BIS	0.12	0.14	0.06	0.08	0.11	0.14	0.05	0.07
	(7.91)**	(9.50)**	(4.96)**	(5.90)**	(20.71)**	(23.61)**	(7.41)**	(10.16)**
Both Advanced	0.18	0.15	0.14	0.17	0.22	0.20	0.18	0.20
	(8.14)**	(5.12)**	(6.81)**	(6.39)**	(25.20)**	(20.31)**	(15.28)**	(16.08)**
FED Shadow Rate	−0.10	−0.09	−0.11	−0.11	−0.10	−0.11	−0.11	−0.13
Cycle	(3.42)**	(3.00)**	(2.80)**	(2.65)**	(24.80)**	(28.21)**	(20.96)**	(25.04)**
VIX	0.01	0.01	0.02	0.02	0.01	0.01	0.02	0.01
	(4.12)**	(3.74)**	(3.74)**	(3.54)**	(34.06)**	(22.33)**	(33.30)**	(21.92)**
Financial Openness		0.15		−0.03		0.18		−0.01
Min.[a]		(4.63)**		(1.29)		(24.47)**		(0.84)
Real Business Cycle			0.04	0.03			0.06	0.05
Synchronization			(3.41)**	(2.49)*			(9.26)**	(7.66)**
Constant	−0.08	−0.17	−0.10	−0.10	−0.31	−0.34	−0.10	
	(1.55)	(2.61)**	(1.35)	(1.23)	(4.75)**	(5.19)**	(6.95)**	
R^2-Overall	0.06	0.06	0.08	0.07	0.10	0.12	0.11	0.12
N	85,374	72,924	45,576	39,029	85,374	72,924	45,576	39,029

[a]Minimum of the measure is used.

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$. Country fixed effects are used for IV GMM regression analysis.

attend the GEM have significantly higher levels of coordination. We also conclude that the co-movement of monetary policies among advanced country pairs is significantly higher than that of other pairs.

4. Robustness Analysis

In this section, we conduct several additional analyses to validate the robustness of our results.

4.1 Time-Series Analysis

Colombia and Peru started to attend the GEM in 2012. This feature allows us to conduct a robustness analysis by examining structural changes in the correlation between other GEM attending countries and Colombia and Peru. We investigate whether the monetary policy coordination between GEM countries and Colombia and Peru is different after April 2012 when the central bank governors of Colombia and Peru started to attend the GEM meetings. Table 2 displays the estimation results of the following regression equation:

$$\rho_{GEM,\tau}^{Colombia,Peru} = \beta_0 + \beta_1 Become\ Member_\tau + B\theta_\tau + \varepsilon_{GEM,\tau}. \quad (3)$$

Table 2. Time-Series Analysis with Colombia and Peru

Become Member	0.25
	(2.63)**
Federal Reserve Shadow Rate Cycle	−0.56
	(10.30)**
VIX	0.02
	(3.82)**
Financial Openness Min.	−0.11
	(3.79)**
Constant	−0.14
	(1.40)
R^2	0.18
N	2,622

Note: $^*p < 0.05$; $^{**}p < 0.01$.

$\rho_{GEM,\tau}^{Colombia,Peru}$ is the time-varying PCC of Colombia and Peru with other GEM countries. $Become\ Member_\tau$ is the dummy variable which is one after April 2012. Table 2 shows that the correlation of monetary policy actions between GEM participants and Colombia and Peru increased significantly after April 2012 when Colombia and Peru started to attend the GEM meetings.

The significant and positive coefficient of $Become\ Member_\tau$ confirms the main result presented in table 1 using a different regression specification. Monetary policy actions of Colombia and Peru significantly became more synchronized with other GEM attendees after they started to attend the meetings and had access to higher means of communication with other GEM central bankers.

4.2 Using Extended Data until 2003

We conduct an additional robustness analysis by extending the data set. The BIS Annual Reports disclose the GEM participants since 2009. We contacted the officials at the BIS about the list of GEM members before 2009. The officials at the BIS stated that the list of member countries did not change since 2003. They did not provide further information about the GEM attendants before 2003. Therefore, we estimate the coefficients of equation (2) by employing a data set that starts from April 2003. A major drawback of the extended data set is that interest rate is available only for forty-three countries—twenty-nine GEM members and fourteen non-GEM countries. Table 3 displays the panel and HB-IV GMM estimation results.

The coefficient of the *Both BIS* dummy variable is significant, with a positive coefficient indicating that central banks that attend the GEM have significantly higher levels of coordination. We also conclude that the co-movement of monetary policies among advanced country pairs is significantly higher than that of other pairs for the extended sample period.

4.3 Measuring Monetary Policy Using First Differences of Money Market Rates

Several studies like Kuttner (2001) and Bernanke and Kuttner (2005) employ the first difference of the monthly federal funds rate

Table 3. Robustness Analysis: Empirical Estimation Using Data Starting from 2003

	Random-Effects Panel				**HB-IV GMM**			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Both BIS	0.05	0.06	0.09	0.10	0.06	0.06	0.12	0.11
	(5.68)**	(6.72)**	(6.66)**	(6.88)**	(9.99)**	(9.34)**	(13.44)**	(11.98)**
Both Advanced	0.05	0.05	0.07	0.09	0.01	−0.01	0.02	0.01
	(4.29)**	(4.12)**	(4.21)**	(5.16)**	(0.47)	(0.90)	(0.91)	(0.60)
FED Shadow Rate	−0.05	−0.06	−0.10	−0.10	−0.05	−0.07	−0.10	−0.12
Cycle	(3.52)**	(3.81)**	(3.70)**	(3.85)**	(24.81)**	(32.58)**	(20.80)**	(23.64)**
VIX	0.00	0.00	−0.00	−0.00	0.00	−0.00	0.00	−0.00
	(0.90)	(0.60)	(0.00)	(0.29)	(7.27)**	(1.59)	(0.22)	(7.38)**
Financial Openness		0.01		0.02		0.04		0.01
Min.		(0.86)		(1.53)		(5.02)**		(0.94)
Real Business Cycle			−0.04	−0.05			0.04	0.02
Synchronization			(5.66)**	(6.69)**			(3.87)**	(1.60)
Constant	0.20	0.21	0.22	0.23	−0.04	0.02	0.25	0.35
	(3.98)**	(4.11)**	(3.80)**	(3.81)**	(1.02)	(0.49)	(16.20)**	(22.09)**
R^2-Overall	0.02	0.02	0.02	0.03	0.05	0.06	0.05	0.06
N	73,260	67,458	30,786	27,564	73,260	67,458	30,786	27,564

Notes: $^*p < 0.05$; $^{**}p < 0.01$. Analysis conducted with forty-three countries. Country fixed effects are used for IV GMM regression analysis.

to gauge the changes in monetary policy. Accordingly, we conduct an additional robustness analysis and calculate correlation coefficients between first differences of money market rates of country pairs to assess the level of monetary policy coordination. We use this alternative coordination measure, $\rho_{a,b,\tau}^{first\ dif}$, as the dependent variable in our main regression specification presented in equation (2). Table 4 shows the results.

Table 4 validates the main results of the paper presented in table 1. The coefficient of the *Both BIS* dummy variable is significant, with a positive coefficient indicating that central banks that attend the GEM have significantly higher levels of coordination. Both random-effects and HB-IV estimations produce similar results.

4.4 Floating Exchange Rate Regime Countries

We conduct additional robustness analysis by focusing on thirty-seven countries with floating exchange rate regimes as listed in AREAERs of the IMF. Among thirty-seven countries, seventeen are GEM attendants, ten are GEM observers, and ten countries do not attend the GEM.[11] Table 5 displays the panel and HB-IV GMM estimation results for floating exchange rate regime countries.

The coefficient of the *Both BIS* dummy variable is significant, with a positive coefficient indicating that central banks that attend the GEM have significantly higher levels of coordination. We also conclude that the co-movement of monetary policies among advanced country pairs is significantly higher than that of other pairs for floating exchange rate regime countries.

4.5 Principal Component Analysis

Our final robustness analysis uses principal component analysis and examines whether common factors of interest rates change with GEM participation. We follow studies like Kritzman et al. (2011)

[11] We display countries with floating exchange rate regimes in table 8 in the appendix.

Table 4. Robustness Analysis: Empirical Estimation Using First Differences of Money Market Rates

	Random-Effects Panel				HB-IV GMM			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Both BIS	0.04	0.04	0.02	0.03	0.04	0.04	0.03	0.04
	(7.62)**	(8.68)**	(4.25)**	(5.55)**	(13.03)**	(13.59)**	(8.82)**	(9.94)**
Both Advanced	0.01	0.01	0.02	0.03	0.05	0.05	0.06	0.07
	(1.19)	(0.57)	(2.65)**	(3.05)**	(10.81)**	(8.90)**	(9.56)**	(10.64)**
FED Shadow Rate	−0.07	−0.08	−0.09	−0.10	−0.07	−0.08	−0.09	−0.10
Cycle	(8.27)**	(10.09)**	(7.71)**	(9.19)**	(38.66)**	(41.04)**	(34.50)**	(37.11)**
VIX	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00
	(0.64)	(2.70)**	(0.76)	(2.48)*	(3.40)**	(11.95)**	(3.68)**	(11.84)**
Financial Openness		0.01		−0.03		0.02		−0.03
Min.		(3.44)**		(5.92)**		(7.10)**		(7.01)**
Real Business Cycle			0.00	−0.00			−0.00	−0.01
Synchronization			(0.17)	(0.45)			(1.08)	(1.51)
Constant	0.05	0.08	0.07	0.12	−0.07	−0.05	0.12	0.20
	(2.56)**	(5.08)**	(3.12)**	(5.94)**	(6.69)**	(4.51)**	(17.26)**	(22.87)**
R^2-Overall	0.03	0.03	0.04	0.04	0.08	0.09	0.09	0.11
N	85,374	72,924	45,576	39,029	85,374	72,924	45,576	39,039

Notes: $*p < 0.05$; $**p < 0.01$. Country fixed effects are used for IV GMM regression analysis.

Table 5. Robustness Analysis: Empirical Estimation Using Floating Exchange Rate Regime Countries

	Random-Effects Panel				HB-IV GMM			
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Both BIS	0.15	0.17	0.11	0.13	0.10	0.11	0.07	0.07
	(7.00)**	(7.31)**	(6.01)**	(6.02)**	(13.06)**	(13.08)**	(7.73)**	(7.58)**
Both Advanced	0.09	0.10	0.06	0.09	0.13	0.18	0.11	0.15
	(5.23)**	(3.83)**	(3.98)**	(3.76)**	(9.95)**	(12.29)**	(6.40)**	(8.43)**
FED Shadow Rate	−0.11	−0.11	−0.11	−0.12	−0.10	−0.12	−0.12	−0.15
Cycle	(2.69)**	(2.73)**	(2.35)*	(2.64)**	(15.91)**	(19.21)**	(15.76)**	(20.15)**
VIX	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.01
	(3.86)**	(3.57)**	(4.12)**	(3.78)**	(29.61)**	(18.92**)	(29.40)**	(18.84)**
Financial Openness		0.00		−0.05		−0.11		−0.18
Min.		(0.13)		(2.13)*		(8.39)**		(10.86)**
Real Business Cycle			−0.02	−0.03			−0.02	−0.03
Synchronization			(1.42)	(2.05)*			(2.53)*	(3.80)**
Constant	−0.10	−0.9	−0.12	−0.05	−0.24	0.01	−0.26	0.08
	(1.37)	(1.18)	(1.42)	(0.54)	(16.13)**	(0.46)	(13.34)**	(3.40)**
R^2-Overall	0.08	0.08	0.10	0.10	0.12	0.15	0.12	0.13
N	39,497	33,017	25,058	21,041	39,497	33,017	25,058	21,041

Notes: $^*p < 0.05$; $^{**}p < 0.01$. Country fixed effects are used for IV GMM regression analysis.

Table 6. Robustness Analysis: Comparison of Principal Components of the GEM Participant and non-GEM Countries

Component	GEM			Non-GEM		
	Eigenvalue	Proportion	Cumulative	Eigenvalue	Proportion	Cumulative
1	16.91	0.63	0.63	18.98	0.43	0.43
2	3.68	0.14	0.77	6.91	0.16	0.59
3	2.63	0.10	0.87	4.7	0.11	0.70
4	1.41	0.05	0.92	3.39	0.08	0.78
5	0.96	0.04	0.96	1.98	0.05	0.83

and Eichengreen et al. (2012)[12] and calculate principal components of money market rates of the GEM participant and non-GEM countries separately. We compare the variance accounted for by principal components for both GEM participant and non-GEM money market rates. See table 6.

Kritzman et al. (2011) uses total variance of asset returns explained by a fixed number of principal components to measure the extent that financial markets are "tightly coupled." We compare the percentage of variation explained by the first five principal components. Table 5 shows that the first five principal components account for 96 percent of variation of the GEM participants and 83 percent of non-GEM countries. Similarly, the first principal component explains 63 percent and 43 percent of the GEM and non-GEM money market rate variation. Accordingly, we conclude that rates of GEM participants are more connected than those of non-GEM participants.

5. Conclusion

We examine the existence and level of international monetary policy coordination using a novel identification specification. We investigate whether communication at the BIS GEM increases co-movement of policy actions of the central banks. We conclude that monetary policy actions of central banks where the governor attends the GEM are significantly more correlated. Hence, communication at the BIS promotes policy coordination. Additionally, we show that monetary policy actions of Colombia and Peru became significantly more correlated with other GEM members after they started to attend the meetings. We conduct several robustness analyses by using an extended data set, employing an alternative monetary policy measure, focusing on floating exchange rate regime countries, and implementing principal component analysis. These analyses confirm the robustness of our results.

[12]Eichengreen et al. (2012) use principal component analysis to extract the common factors underlying weekly variations in the credit default swap spreads of forty-five European and U.S. banks.

Appendix

Table 7. List of Countries

Country	BIS GEM Membership
Angola	Non-GEM
Argentina	GEM Attendant
Armenia	Non-GEM
Australia	GEM Attendant
Bolivia	Non-GEM
Brazil	GEM Attendant
Canada	GEM Attendant
Chile	GEM Observer
Colombia	GEM Observer
Congo, Dem. Rep. of	Non-GEM
Croatia	Non-GEM
Czech Republic	GEM Observer
Dominican Republic	Non-GEM
Euro Area	GEM Attendant
Georgia	Non-GEM
Hungary	GEM Observer
Iceland	Non-GEM
India	GEM Attendant
Indonesia	GEM Attendant
Israel	GEM Observer
Jamaica	Non-GEM
Japan	GEM Attendant
Korea, Republic of	GEM Attendant
Malaysia	GEM Attendant
Mauritius	Non-GEM
Mexico	GEM Attendant
Moldova	Non-GEM
Mozambique	Non-GEM
New Zealand	GEM Observer
Norway	GEM Observer
Pakistan	Non-GEM
Papua New Guinea	Non-GEM
Paraguay	Non-GEM
Peru	GEM Observer
Philippines	GEM Observer
Poland	GEM Attendant
Romania	GEM Observer

(*continued*)

Table 7. (Continued)

Country	**BIS GEM Membership**
Russian Federation	GEM Attendant
Serbia, Republic of	Non-GEM
Singapore	GEM Attendant
South Africa	GEM Attendant
Sri Lanka	Non-GEM
Sweden	GEM Attendant
Switzerland	GEM Attendant
Tajikistan	Non-GEM
Thailand	GEM Attendant
Tunisia	Non-GEM
Turkey	GEM Attendant
Ukraine	Non-GEM
United Kingdom	GEM Attendant
United States	GEM Attendant
Uruguay	Non-GEM
Vanuatu	Non-GEM

Table 8. Floating Exchange Rate Regime Countries

Country	BIS GEM Membership	Notes about Exchange Rate Regime
Armenia	Non-GEM	Armenia moved to crawl-like arrangement from floating arrangement in April 2013.
Australia	GEM Attendant	
Brazil	GEM Attendant	
Canada	GEM Attendant	
Chile	GEM Observer	
Colombia	GEM Observer	
Congo, Dem. Rep. of	Non-GEM	Democratic Republic of the Congo moved to other managed arrangement in November 2011.
Czech Republic	GEM Observer	Czech Republic moved to other managed arrangement in November 2013.
Euro Area	GEM Attendant	
Georgia	GEM Attendant	Georgia adopted a floating exchange rate regime in years 2010, 2011, 2013, and 2014.
Hungary	GEM Observer	
Iceland	Non-GEM	
India	GEM Attendant	
Indonesia	GEM Attendant	Indonesia adopted a crawl-like regime in the July 2012–August 2013 period.
Israel	GEM Observer	
Japan	GEM Attendant	
Korea, Republic of	GEM Attendant	
Mauritius	Non-GEM	
Mexico	GEM Attendant	
Moldova	Non-GEM	
Mozambique	Non-GEM	
New Zealand	GEM Observer	
Norway	GEM Observer	
Papua New Guinea	Non-GEM	
Paraguay	Non-GEM	Paraguay implemented other managed arrangement regime in years 2010–12.
Peru	GEM Observer	
Philippines	GEM Observer	
Poland	GEM Attendant	
Romania	GEM Observer	
Serbia, Republic of	Non-GEM	
South Africa	GEM Attendant	
Sweden	GEM Attendant	
Thailand	GEM Attendant	
Turkey	GEM Attendant	
United Kingdom	GEM Attendant	
United States	GEM Attendant	
Uruguay	Non-GEM	

References

Aizenman, J., M. D. Chinn, and H. Ito. 2008. "Assessing the Emerging Global Financial Architecture: Measuring the Trilemma's Configurations over Time." NBER Working Paper No. 14533.

Bernanke, B. S. 2014. "Global Monetary Policy: A View from Emerging Markets." The Brookings Institution. Available at http://www.brookings.edu/events/2014/04/10-global-monetary-policy-view-from-emerging-markets.

Bernanke, B. S., and K. N. Kuttner. 2005. "What Explains the Stock Market's Reaction to Federal Reserve Policy?" *Journal of Finance* 60 (3): 1221–57.

Blanchard, O., J. D. Ostry, and A. R. Gosh. 2013. "International Policy Coordination: The Loch Ness Monster." IMFDirect Blog, December 15.

Borio, C. E. V., and G. Toniolo. 2006. "One Hundred and Thirty Years of Central Bank Cooperation: A BIS Perspective." BIS Working Paper No. 197.

Chinn, M. D., and H. Ito. 2006. "What Matters for Financial Development? Capital Controls, Institutions, and Interactions." *Journal of Development Economics* 81 (1): 163–92.

Edwards, S. 2015. "Monetary Policy Independence under Flexible Exchange Rates: An Illusion?" *The World Economy* 38 (5): 773–87.

Eichengreen, B., A. Mody, M. Nedeljkovic, and L. Sarno. 2012. "How the Subprime Crisis Went Global: Evidence from Bank Credit Default Swap Spreads." *Journal of International Money and Finance* 31 (5): 1299–1318.

Flood, R. P., and A. K. Rose. 2010. "Inflation Targeting and Business Cycle Synchronization." *Journal of International Money and Finance* 29 (4): 704–27.

Hofmann, B., and E. Takáts. 2015. "International Monetary Spillovers." *BIS Quarterly Review* (September): 105–18.

Kara, A. H. 2015. "Interest Rate Corridor and the Monetary Policy Stance." Research Notes in Economics No. 1513, Research and Monetary Policy Department, Central Bank of the Republic of Turkey.

Kritzman, M., Y. Li, S. Page, and R. Rigobon. 2011. "Principal Components as a Measure of Systemic Risk." *Journal of Portfolio Management* 37 (4): 112–26.

Kuttner, K. N. 2001. "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market." *Journal of Monetary Economics* 47 (3): 523–44.

Lewbel, A. 2012. "Using Heteroscedasticity to Identify and Estimate Mismeasured and Endogenous Regressor Models." *Journal of Business and Economic Statistics* 30 (1): 67–80.

Rey, H. 2015. "Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence." NBER Working Paper No. 21162.

Vegh, C. A., and G. Vuletin. 2012. "Overcoming the Fear of Free Falling: Monetary Policy Graduation in Emerging Markets." NBER Working Paper No. 18175.

Wu, J. C., and F. D. Xia. 2016. "Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound." *Journal of Money, Credit and Banking* 48 (2–3): 253–91.