

# QE: Implications for Bank Risk-Taking, Profitability, and Systemic Risk\*

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In the aftermath of the subprime mortgage bubble, the Federal Reserve implemented large-scale asset purchase (LSAP) programs that aimed to increase bank liquidity and lending. The excess liquidity created by quantitative easing (QE), in turn, may have stimulated bank risk-taking in search of higher profits. Using comprehensive data on balance sheets, risk measures, and daily market returns in the U.S., we investigate the link between QE, bank risk-taking, profitability, and systemic risk. We find heterogeneous effects across different rounds of QE. In particular, during the third round of QE, banks that were more exposed to unconventional monetary policy through mortgage-backed securities (MBS) purchases increased their risk-taking behavior and profitability. However, these banks also reduced their contribution to systemic risk, indicating that the implementation of QE had an overall stabilizing effect on the banking sector. These results highlight the different distributional effects of QE.

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## 1. Introduction

How does quantitative easing (QE) affect individual banks and overall financial stability? Our paper seeks to examine various dimensions of this question. Central banks have traditionally employed

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short-term interest rates to stabilize inflation and economic fluctuations. The period preceding the Global Financial Crisis (GFC) of 2007–08 featured low monetary policy rates that led to a deterioration of bank lending standards and subsequent increases in risk-taking (Dell’Ariccia, Laeven, and Marquez 2014; Bernanke et al. 2020). The persistently low real interest rate environment fueled a boom in asset prices and securitized credit that led financial institutions to take on increasing risk and leverage, thereby extending loans to borrowers with minimum or no credit history (Altunbas, Gambacorta, and Marques-Ibanez 2010; Paligorova and Santos 2017). Hence, banks are considered to have played a significant role in the buildup and spread of systemic risk (Nijskens and Wagner 2011). The Financial Stability Board defines systemic risk as “a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy” (Financial Stability Board 2009).

The Federal Reserve (Fed) responded to the zero lower bound and subsequent worsening of the economic crisis by embarking on large-scale asset purchase programs, often referred to as QE, with the intention of providing additional monetary stimulus, restoring stability, and reducing systemic risk. The introduction of such unconventional policy measures rekindled debate on the impact of monetary policy on risk-taking, performance, and stability of the banking sector. Empirical evidence suggests that QE can have both benefits and costs with varying effects on economic outcomes.<sup>1</sup> On the one hand, QE can induce banks to increase their appetite for risk by extending loans to borrowers with bad credit history or no credit history at all (i.e., risky borrowers). Alternatively, QE may reduce bank risk by increasing bank lending that boosts investment and economic growth. This strengthens banks’ resistance to exogenous shocks. Thus, the net effect of QE on banking-sector stability is not

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<sup>1</sup>While quantitative easing has shown to boost lending and liquidity in the banking sector (Rodnyansky and Darmouni 2017; Chakraborty, Goldstein, and Mackinlay 2020; Luck and Zimmermann 2020), this can also come at the cost of increased risk-taking by banks (Kandrac and Schlusche 2021; Kurtzman, Luck, and Zimmermann 2022).

obvious and depends on whether the benefits of QE outweigh its costs.

The key question that we ask is: What is the impact of QE on individual bank risk-taking, bank profitability, and systemic risk? Although recent empirical studies examine the effects of monetary policy on individual bank risk,<sup>2</sup> we are aware of relatively few that address systemic risk. So far the literature is split on the role of bailouts in either increasing or decreasing systemic risk. Evidence suggests that bailouts can reduce systemic risk either through a higher charter value effect<sup>3</sup> (Cordella and Yeyati 2003) or through a reduction in undiversifiable contagion risk across banks (Diamond and Rajan 2005; Dell’Ariccia and Ratnovski 2013; Choi 2014). Others predict that bailouts can increase systemic risk by exacerbating moral hazard problems and creating strategic complementarities among banks, which encourage coordinated risk-taking behavior (Acharya and Yorulmazer 2007a, 2007b; Diamond and Rajan 2009a; Farhi and Tirole 2012). Berger, Roman, and Sedunov (2017) employ the U.S. Troubled Assets Relief Program (TARP) as an event study and provide discussion on the topic. To this end, our study is one of the first to provide a distributional perspective on the implications of QE and its effect on systemic risk. Our analysis moreover explores potential asymmetries in the effects of different rounds of QE by the Fed. We focus in particular on purchases of mortgage-backed securities (MBS) since this was the primary asset tool employed. The idea is that such purchases should directly improve the risk profile and liquidity of banks’ overall assets. According to the Federal Open Market Committee (FOMC), based on FRB/US model simulations, purchases of agency MBS were more likely to provide greater economic stimulus than purchases of long-term Treasuries of comparable size (Gagnon and Holscher 2008). The former, therefore, were expected to be of central importance.<sup>4</sup>

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<sup>2</sup>See Altunbas, Gambacorta, and Marques-Ibanez (2010), Delis and Kouretas (2011), Dell’Ariccia, Laeven, and Marquez (2014), and Bikker and Vervliet (2018).

<sup>3</sup>A bank’s charter value is an indicator of the bank’s incentive to take risk or private cost of failure. See Keeley (1990).

<sup>4</sup>In unreported additional checks, we find that purchases of Treasuries by the Fed did not have the same strong impact on risks and profitability in the banking sector as MBS purchases. Indeed, Krishnamurthy and Vissing-Jorgensen (2011)

We study the heterogeneous impact of QE on bank risk-taking, profitability, and systemic risk using a sample of U.S. bank holding companies over the 2006:Q1–2014:Q4 period. We first assess the impact of QE on bank risk-taking by employing time-varying Z-scores, a classic balance sheet measure of firm riskiness. Second, we explore whether banks increase their risk appetite to lend more during various QE episodes in search of higher profits. Finally, we examine the effects of QE on systemic risk within the U.S. financial sector. Section 3 discusses the three variables of interest in detail.

To identify the effects of QE, we closely follow the empirical strategy of Rodnyansky and Darmouni (2017) and Luck and Zimmermann (2020). We exploit the cross-sectional variation across holdings of MBS for commercial banks in our sample. The identification rests on the idea that banks with higher MBS holdings benefit more from the Fed's asset purchases of securities.<sup>5</sup> We adopt a fixed-effects identification strategy that relies on the interaction of cross-sectional variation among banks in their MBS holdings and the corresponding QE time dummies. We employ several definitions based on the ratio of MBS-to-total-assets prior to QE in order to classify banks into treated and control groups, respectively, and investigate the differential effects of the policy across banks.

Our baseline statistics offer preliminary insight into the interrelations of the three variables of interest. We then run separate regressions for risk-taking, profitability, and systemic risk, and find that banks with higher MBS holdings increased risk-taking during the third round of QE (QE3) relative to banks that were unaffected by large-scale asset purchases.<sup>6</sup> This is consistent with the previous literature where Gambacorta (2009), Altunbas, Gambacorta,

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conclude that focusing primarily on Treasuries as a policy target is inappropriate, as QE functions through various channels that affect specific asset classes differently.

<sup>5</sup>There are several reasons why banks that held more mortgage-backed securities benefited more from the large-scale asset programs. First, during the three waves of QE, the Fed focused on easing the deterioration in the MBS market by lowering yields and increasing the prices of banks' current asset holdings, thereby improving the balance sheets of banks that held higher shares of mortgage-backed securities. Second, banks with more MBS sold to the Fed saw a higher increase in reserves, which should have shifted their loan supply (Kandrac and Schlusche 2021).

<sup>6</sup>We note that risk-taking is not necessarily undesirable, unlike risk-shifting.

and Marques-Ibanez (2010), Delis and Kouretas (2011), and more recently Kandrac and Schlusche (2021) find a negative relation between monetary policy (conventional and unconventional) and bank risk-taking, thus confirming the existence of the bank risk-taking channel.

Furthermore, we show that the same banks enjoyed higher profits during QE3 and suggest a possible connection between increased bank risk-taking and profit maximization. Finally, we document the effects of QE on systemic risk and financial stability. Our evidence suggests that banks with relatively more MBS to total assets reduce their contributions to systemic risk after the implementation of QE3. This implies that asset purchase programs were supportive in the recovery of the banking sector after the GFC. Our results are consistent with Berger, Roman, and Sedunov (2017), who investigate the impact of bailouts on banks' contribution to overall financial stability. With our findings, we suggest a mechanism of monetary policy transmission where banks reduce their contribution to systemic risk as a result of high risk-taking and subsequent increases in profits. Our empirical findings are robust to alternative methodologies, including a system of equations approach, and other robustness tests.

The remainder of the paper is organized as follows. Section 2 describes our theoretical framework, followed by Section 3, which discusses the data and identification strategy. Section 4 presents our results, while Section 5 concludes.

## 2. Literature Overview

In this section, we review the theoretical implications of monetary expansion for (i) bank risk-taking, (ii) bank profitability, and (iii) systemic risk.

### 2.1 *Bank Risk-Taking*

The effect of monetary policy on banks' risk-taking behavior is of special interest, as excessive risk-taking by commercial banks is considered to be one of the factors that led to the outbreak of the

GFC.<sup>7</sup> Borio and Zhu (2012) refer to the “*risk-taking channel*” of monetary policy as prolonged periods of low interest rates that can alter the risk perceptions and risk tolerance of financial institutions. The channel operates on the basis of valuations, incomes, and cash flows, where an expansionary monetary policy drives up the value of real and financial collateral and increases bank capacity to extend risky loans.

The empirical literature on the risk-taking channel has been widely studied by examining key policy rates. Several studies, including those of Dell’Ariccia and Ratnovski (2013), Ioannidou, Ongena, and Peydró (2014), Jiménez et al. (2014), and Paligorova and Santos (2017), show that banks loosen lending standards and increase credit supply by extending loans to risky borrowers during monetary expansions. The literature adopts several measures for risk-taking ranging from internal ratings on borrowers’ repayment capacity, default probabilities, time to default (Ioannidou, Ongena, and Peydró 2014), and change in expected default frequency (Gambacorta 2009) to Z-scores (Laeven and Levine 2009; Schaeck and Čihák 2010; Beck, De Jonghe, and Schepens 2013). Recent work on the topic is concerned with the impact of LSAPs on the risk-taking behavior of commercial banks. In their empirical analyses, Kandrak and Schlusche (2021) and Kurtzman, Luck, and Zimmermann (2022) use microdata (bank and loan level) and find that various QE programs led to higher total loan growth and an increase in the share of riskier loans within banks’ portfolios.

There are several reasons why QE may have promoted risk-taking. As a response to QE and excess reserves in balance sheets, banks may choose to maintain their profit margins and incomes by searching for yield in lending (Borio and Zhu 2012; Jiménez et al. 2014; Kandrak and Schlusche 2021). Since the main motive of QE was to directly lower long-term interest rates and thus stimulate the economy, lower yields incentivize banks to accelerate risk-taking activity (Rajan 2006). The various QE policies might have induced

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<sup>7</sup>Studies such as those of Acharya and Richardson (2009) and Diamond and Rajan (2009b) assert that very long periods of low interest rates, accompanied by an abundance of global liquidity, would have led financial companies to behave in a riskier way. This was indeed a contributing factor in the development of the Global Financial Crisis.

financial market participants to reallocate portfolios toward riskier and more profitable projects, thereby leading to excessive risk-taking (Abbate and Thaler 2019). Finally, monetary policy can affect bank risk-taking through leverage decisions. Dell’Ariccia, Laeven, and Marquez (2014) present a theoretical model in which a reduction in the risk-free interest rate reduces the cost of holding required reserves, thus leading to higher leverage and increased risk-taking by banks. However, directly after the GFC, it is conceivable that banks may have used the initial stages of QE (e.g., first round) to improve or stabilize their own balance sheet risk profiles by not engaging in risky lending/investment, with a view to restoring confidence in their operations. Asymmetric effects on bank risk-taking across different QE rounds may also be expected if yields are differentially affected across these phases. Krishnamurthy and Vissing-Jorgensen (2011, 2014), for instance, demonstrate that the second round of QE had very weak effects on yields compared to those of the third round. The authors also illustrate that MBS yields were more strongly affected than Treasury yields by QE, suggesting that Fed purchases of MBS had more potent effects on banks than Treasury purchases. They contend that purchases of the former are crucial in attenuating corporate credit risk.

As the Fed buys assets from banks through QE, it increases assets (securities) on its balance sheet, concurrently crediting banks’ reserve accounts. By providing liquidity in the banking sector, QE made it easier and cheaper for banks with relatively high MBS to extend loans to nonfinancial firms and households, thereby inducing banks to increase their risk-taking capacity.

## *2.2 Bank Profitability*

While risk-taking behavior is an intended consequence of unconventional monetary policy, reach for yield is a form of risk-taking, a way to achieve higher profits and performance. An expansionary monetary policy induces banks to increase their holdings of risky assets in order to “reach for yield” (Rajan 2006; Borio and Zhu 2012). Reaching for yield means that banks maximize the yield spread without paying adequate regard to risk—by obtaining a higher return on their asset holdings, by paying a lower return to their creditors, or by engaging in both practices. In other words, it can be defined as

the agents' propensity to buy riskier assets in order to achieve higher yields and profits.<sup>8</sup>

Interest in the relation between monetary policy and bank profitability has gained momentum since the GFC. Accommodative monetary policy creates bank liquidity and lowers the cost of debt, thereby increasing bank capital, lowering loan loss provisioning, and increasing profitability (Bernanke and Gertler 1995; Bernanke 2007; Freixas, Martin, and Skeie 2011). At the same time, periods of monetary expansion can have negative effects on bank profits. Additional monetary stimulus when interest rates are already too low can squeeze banks' net interest (profit) margins, in turn diminishing their net worth and credit supply. Persistently low interest rates may place chronic downward pressure on profitability that eventually more than offsets banks' initial capital gains and likewise hinders the credit supply. Importantly, there exists a "reversal interest rate" at which accommodative monetary policy can become contractionary for lending (Abadi, Brunnermeier, and Koby 2023). Inertia at low interest rate levels can thus hamper the monetary policy transmission mechanism (Alessandri and Nelson 2015; Brunnermeier and Koby 2016; Borio, Gambacorta, and Hofmann 2017). In order to improve net interest margins when interest rates are too low for too long, banks might reduce their funding rates to compensate for low lending rates. The net effect of monetary policy measures on bank profitability, therefore, is not obvious and remains an empirical question.

This paper further investigates the impact of QE on bank profitability and, hence, the soundness of the banking sector. Keeley (1990) shows that risk-taking incentives should be lower in more profitable firms, as they stand to lose more shareholder value if downside risks are realized. However, more recently, significant risk-taking in profitable institutions seems to contradict the traditional predictions of corporate finance models (Martynova 2015). In an unconventional monetary policy environment, banks may increase their risk-taking and influence asset valuations in search for higher profits.

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<sup>8</sup>Exploring the drivers of relative finance wages, Velic (2025) finds that financial deregulation also contributed to higher profitability and relative skilled wages in the financial sector, especially in the lead-up to the GFC.

### *2.3 Systemic Risk*

The literature on unconventional monetary policy thus far focuses on the effects of QE on interest rates (Krishnamurthy and Vissing-Jorgensen 2011), bank lending (Rodnyansky and Darmouni 2017; Luck and Zimmermann 2020), risk-taking (Kandrac and Schlusche 2021), and bank liquidity (Kapoor and Peia 2021), with little attempt to investigate the impact of QE on systemic risk. This paper explores the distributional effects of QE by investigating the impact on systemic risk. In particular, we study if QE led financial institutions to increase their risk-taking and profitability, thus providing a cushion to absorb losses and reduce the likelihood of financial distress and bank failure.

Prior to the crisis, Basel regulations and capital ratios were popular tools to measure a bank's risk. However, since the GFC, use of market-based measures of systemic risk has become more prevalent. For instance, Huang, Zhou, and Zhu (2012) uncover the concept of "distress insurance premium" using credit default swaps and equity returns. Similarly, Adrian and Brunnermeier (2011) construct the "CoVaR" that captures the contribution of an institution to the overall systemic risk of the system. Allen, Bali, and Tang (2012) extend the concept of value at risk (VaR) by constructing CATFIN, which links systemic risk to VaR of the financial system. Acharya, Engle, and Richardson (2012) propose the marginal expected shortfall (MES) that depends solely on market-based information and estimates individual bank reactions to the entire stock market when aggregate returns are low. Furthermore, Acharya et al. (2017) estimate systemic expected shortfall (SES), which merges both market and balance sheet information to measure a bank's propensity to be undercapitalized under stress conditions. We employ SES for our analysis. Details on the construction of the measure are provided in the next section.

## **3. Data and Methodology**

Our data come from the quarterly Consolidated Financial Statements for Bank Holding Companies (BHCs) in the United States, which are available from the Federal Reserve Bank of Chicago. All BHCs are subject to regulation by the Federal Reserve Board of

Governors under the Bank Holding Company Act of 1956 and Regulation Y. Our data cover the period 2006:Q1 to 2014:Q4 and include information on the financial condition of the BHCs such as balance sheet items, off-balance-sheet exposures, statistics on different types of loans, etc.<sup>9</sup> We omit observations with missing values for total assets. This leaves us with a final sample of 1,438 unique BHCs and 31,467 BHC-quarter observations.

We match these data with market data obtained from the Center for Research in Security Prices (CRSP), which provides U.S. stock data for all publicly listed institutions (including financial firms) with end-of-day and month information on all primary listings (NYSE, NYSE MKT, NASDAQ) along with basic market indices. The data include multiple company identifiers—including PERMNO, PERMCO, and GVKEY—that are used to match with bank-level data. Each BHC's identifier was matched with the CRSP permanent company identifier (PERMCO) using the CRSP-FRB Link provided by the Federal Reserve Bank of New York.<sup>10</sup> In order to fully utilize the two data sets, we employ fuzzy matching for all companies that did not have a PERMCO available.<sup>11</sup> Our merged data comprise information on daily returns for 743 unique bank holding companies, with 11,738 BHC-quarter observations in the sample.<sup>12</sup>

To estimate the impact of QE on risk-taking and systemic risk, several key measures are constructed separately from estimated

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<sup>9</sup>The reporting forms have changed a number of times over the sample period, causing changes to some variables available in the raw data over time. Where reporting changes have affected variables of interest, we have manually traced these changes through the reporting form and merged data as appropriate.

<sup>10</sup>According to the Federal Reserve Bank of New York, the CRSP and BHC data, when merged using PERMCOs, will yield 1,430 unique BHCs from June 30, 1986 to December 31, 2017. Available at [https://www.newyorkfed.org/research/banking\\_research/datasets.html](https://www.newyorkfed.org/research/banking_research/datasets.html).

<sup>11</sup>These companies were matched based on their names, with a threshold level of 0.95. The matching was further cross-checked by employing different threshold levels (between 0.95 and 1) in order to ascertain the quality of the matching method.

<sup>12</sup>The matched data are used in analyzing the impact of QE on systemic risk contribution by financial firms. Thus, we end up with 288 BHCs and approximately 5,100 BHC-quarter observations after the construction of systemic risk measures.

regressions. First, we compute Z-scores as a measure of bank risk-taking by following Schaeck and Čihák (2010) and Beck, De Jonghe, and Schepens (2013). The Z-score is a classic balance sheet measure of bank riskiness, conceived from the concept of a bank's probability of default. It is often used to capture either the stability of the banking sector (Lee and Hsieh 2014) or the inverse probability of insolvency of a bank (Williams 2016). The Z-score is formally expressed as

$$Z_{i,t} = \frac{ROA_{i,t} + EA_{i,t}}{\sigma_{i,t}^{ROA}}, \quad (1)$$

where  $ROA_{i,t}$  is the return on assets for bank  $i$  at time  $t$  (bank profitability),  $EA_{i,t}$  is the ratio of bank  $i$ 's equity to total assets at time  $t$  (capitalization), and  $\sigma_{i,t}^{ROA}$  is the time-varying variability of returns on assets. A lower Z-score indicates higher bank risk-taking and vice versa. As Z-score data are highly skewed, we employ the natural logarithm of the measure. For brevity, we refer to the natural logarithm of the Z-score as "Z-score" throughout the study. Figure 1 plots the components of the average Z-score over time. Based on gross correlations, the Z-score is most strongly related to the ratio of equity to assets. Second, we examine net interest income and return on assets as measures of profitability, with the latter measure featuring in our robustness checks.

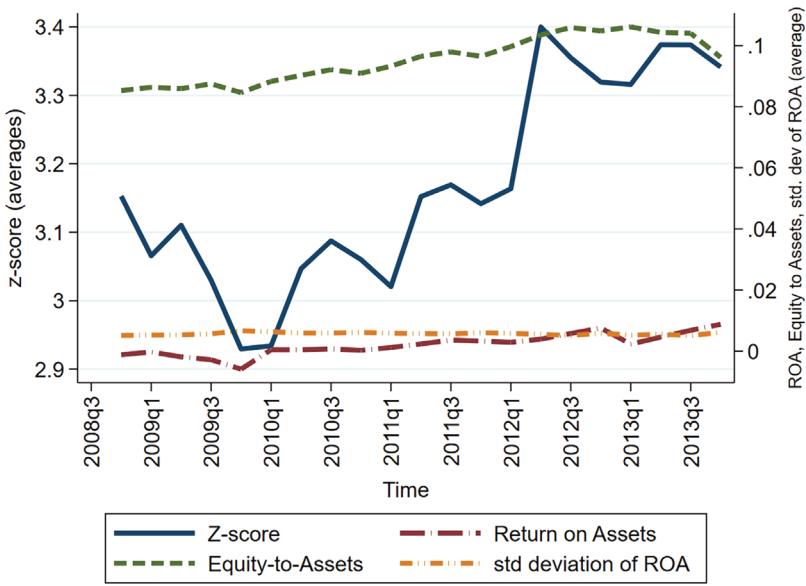
Third, we employ the systemic expected shortfall (SES) measure proposed by Acharya et al. (2017) for systemic risk. SES captures the contribution of individual banks to systemic risk in the banking sector. The measure employs both market and balance sheet information and gauges a bank's propensity to be undercapitalized under stress conditions. Therefore, marginal expected shortfall (MES) and a financial firm's leverage are two significant components in the construction of SES.<sup>13</sup> We calculate MES by taking average returns for a firm on days when the market as a whole is in the tail of its loss distribution:

$$MES_{i,t} = E[R_t^i | R_t^m < C]. \quad (2)$$

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<sup>13</sup>MES depends solely on market-based information and estimates an individual bank's reaction to the entire stock market when aggregate returns are low.

Figure 1. Components of Z-score



Next, leverage is defined as the quasi-market value of assets to market value of equity and is estimated by the standard approximation approach using book liabilities and market equity:

$$LVG_{i,t} = \left[ \frac{(BookAssets_{i,t} - BookEquity_{i,t}) + MarketEquity_{i,t}}{MarketEquity_{i,t}} \right], \tag{3}$$

where  $MarketEquity_{i,t}$  is the number of shares outstanding times the average price of a share for a given quarter, and  $BookAssets_{i,t}$  and  $BookEquity_{i,t}$  are bank characteristics that are available at a quarterly frequency from balance sheet data. Using  $MES_{i,t}$  and  $LVG_{i,t}$ , Acharya et al. (2017) regress the percentage stock returns of U.S. institutions on the given components prior to the crisis and employ an  $SES_{i,t}$  definition of the following form:

$$SES_{i,t} = \hat{a}MES_{i,t} + \hat{b}LVG_{i,t}. \tag{4}$$

We adopt a similar formula and take values of coefficient estimates  $\hat{a}$  and  $\hat{b}$  from Acharya et al. (2017).<sup>14</sup>  $SES_{i,t}$  measures the extent to which a bank is undercapitalized in an event in which the entire financial system is under distress. Thus, increases in  $SES_{i,t}$  indicate increases in banks' expected losses during crisis.

In order to identify the effects of QE on bank risk-taking, profitability, and systemic risk, we employ the fixed-effects estimation methodology and divide our sample into treatment and control groups based on the ratio of MBS-to-total-assets prior to the introduction of QE, i.e., 2007:Q4.<sup>15</sup> Our identification strategy follows Rodnyansky and Darmouni (2017) and exploits cross-sectional variation in MBS holdings across banks. The identification strategy relies on the assumption that banks with higher proportions of MBS to total assets were more affected by the asset purchases. This is corroborated by the fact that banks with more MBS sold to the Fed saw a higher increase in reserves, which should have shifted their loan supplies (Kandrac and Schlusche 2021).

We measure a bank's exposure to QE by the ratio of MBS to total assets.<sup>16</sup> We define treatment group banks as those in the top 25 percent (top quartile) of the MBS-to-total-assets distribution, while control group banks are in the bottom 25 percent (bottom quartile) of the distribution. Figure 2 shows the evolution of the MBS to total assets of treated and control banks separately, indicating that MBS holdings of treated banks (solid line) start to decline immediately after the implementation of QE, while control banks (dashed line) see an increase. We use several other definitions of treatment and control groups based on deciles (top and bottom 10 percent) and the continuous ratio (full sample) of MBS to total assets in 2007:Q4.

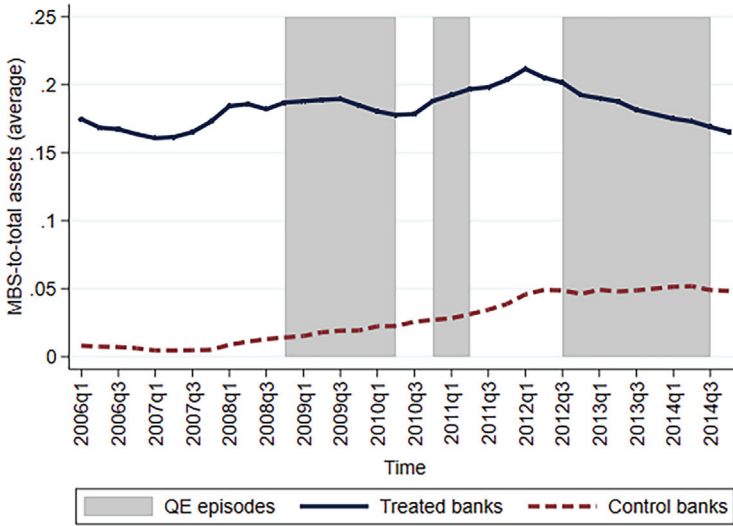
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<sup>14</sup> Additionally, we examine our own estimates of coefficients  $a$  and  $b$  in unreported robustness checks. The results are similar qualitatively.  $MES$  and  $LVG$  tend to exhibit an inverse contemporaneous relation with  $SES$ .

<sup>15</sup> The choice of time period 2007:Q4 minimizes endogeneity since this is more than six months before QE1. The MBS threshold is defined in a particular quarter so that we are able to track the effects for the same set of banks over time. Implementing the treatment definition in alternative quarters just before each of the other two QE episodes yields similar results qualitatively.

<sup>16</sup> We also employ the MBS-to-securities ratio as an alternative measure of a bank's exposure to QE. The results are consistent with the main results since the ratios of MBS to assets and MBS to securities are highly correlated in the sample.

**Figure 2. MBS to Total Assets for Treated and Control Banks**



**Note:** The figure maps the evolution of the ratio of MBS to assets for treated and control banks. Treated banks are banks in the top quartile (top 25 percent) of the MBS-to-total-assets ratio in 2007:Q4, while control banks are in the bottom quartile (bottom 25 percent) of the distribution. Shaded areas highlight the three episodes of QE.

We employ a fixed-effects identification strategy that relies on the interaction of cross-sectional variation among banks in their MBS holdings and the corresponding QE time dummies. Our regression model is given by

$$\begin{aligned}
 Y_{i,t} = & \alpha_i + \beta_t + \rho_{i,t} + \gamma'_1 QE_t + \gamma_2 Treat_i + \theta' Treat_i \\
 & \times QE_t + \delta' X_{i,t-1} + \epsilon_{i,t}.
 \end{aligned}
 \tag{5}$$

$Y_{i,t}$  denotes the dependent variable and is the measure of individual bank risk-taking, profitability, or contribution to systemic risk across our three specifications.  $Treat_i$  is an indicator variable and takes the value of 1 if a bank belongs to the treatment group and 0 otherwise.  $QE'_t = [QE1_t, QE2_t, QE3_t]$  is a vector of time dummies corresponding to the introduction of each QE episode, where

the dummy takes the value of 1 during the episode and 0 otherwise. QE1 corresponds to the period 2008:Q4 (November)–2010:Q2 (June), QE2 to 2010:Q4 (November)–2011:Q2 (June), and QE3 to 2012:Q3 (September)–2014:Q3 (October).  $Treat_i \times QE_t$  is an interaction term between a bank's treatment status and time dummies corresponding to each QE episode. The vector  $\theta$  captures our coefficients of interest, namely the differential impact of each round of QE on the dependent variable in the treated as compared to the control group.<sup>17</sup>

Vector  $X_{i,t-1}$  includes a series of bank-level controls that capture differences in the scale and financial position of banks that might affect their activities. Specifically, we control for bank size (natural logarithm of total assets), liquidity ratio (ratio of cash to total deposits), tier 1 capital ratio to account for the extent to which a bank absorbs potential losses, leverage ratio, and deposit ratio. All control variables are included as lagged terms, and a description of the construction of the same is presented in Table A.1 in Appendix A. Including interactions between controls and the treatment variables does not alter results significantly.

The regression also includes bank fixed effects ( $\alpha_i$ ) to control for fixed differences among banks, and quarterly time fixed effects ( $\beta_t$ ) to control for residual intertemporal differences in common shocks that affect all banks.<sup>18</sup> Examples of shocks affecting all banks during the sample period are the Dodd-Frank Act and Basel Accords (including stress-testing). In addition, we employ state fixed effects ( $\rho_{i,t}$ ) to control for location fixed effects for BHCs as well as any state-specific regulatory policies that might affect banking functions.

While the null hypothesis of cross-sectional independence can be rejected in tests for all regression model residuals, we report in table notes that average and average absolute cross-sectional correlations are quite small, thus making the assumption of independence appropriate in practice (Galstyan and Velic 2017; Pesaran 2021). The summary statistics for our data set and the key variables employed in the study can be seen in Table 1.

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<sup>17</sup>The individual effects of the treatment variable are absorbed by fixed effects in regressions.

<sup>18</sup>Statistically significant time dummies are included in the regression, and there are no multicollinearity issues in the specification.

Table 1. Summary Statistics

Variable	Mean	Standard Deviation	p25	p50	p75	Observations
Treatment Variable: MBS/Total Assets	0.095	0.088	0.026	0.076	0.138	31,754
Dependent Variables: ln( <i>Z-score</i> )	3.38	0.687	3.05	3.417	3.752	27,094
Risk Assets/Assets	0.933	0.064	0.918	0.953	0.972	31,754
ln(Net Interest Income)	10.11	1.37	9.26	9.87	10.61	31,754
Return on Assets	0.095	9.465	0.002	0.005	0.008	28,508
$\Delta$ ln( <i>SES</i> )	-3.1	1.00	-3.3	-3.25	-3.19	5,087
<i>SRI</i> SK	-3.34	13.21	0.63	0.82	1.01	4,843
Bank-Specific Controls: Bank Size	14.176	1.325	13.365	13.768	14.534	31,754
Tier 1 Capital Ratio	13.932	22.608	10.67	12.57	15.03	30,484
Leverage Ratio	9.968	15.371	8.19	9.31	10.63	30,484
Deposits Ratio	0.782	0.113	0.750	0.805	0.849	29,408
Liquidity	0.854	65.42	0.029	0.045	0.083	29,388

**Note:** Summary statistics recorded from 2006:Q1 to 2014:Q4 for all U.S. BHCs. All variables are at quarterly frequency. Variable definitions are provided in Appendix A. Risk assets/assets, return on assets, and *SRI*SK are alternative measures of bank risk-taking, profitability, and systemic risk, respectively, in robustness checks.

**Table 2. Pearson Gross Correlations**

Variable	Z-score	NII	SES
Z-score	1.0000		
NII	-0.0599***	1.0000	
SES	-0.1593***	0.0119	1.0000

**Note:** The variables Z-score and net interest income (NII) are expressed in natural logarithms, while SES is defined as the change in systemic expected short-fall. \*\*\*, \*\*, and \* represent significance at 1 percent, 5 percent, and 10 percent, respectively.

## 4. Results

### 4.1 Baseline Correlations

We present pairwise (Pearson) gross correlations between bank risk-taking, profitability, and systemic risk in Table 2. Although relatively weak, we report a negative correlation between the Z-score and net interest income, indicating that a lower Z-score (higher bank risk-taking) is associated with higher net interest income (profitability). Similarly, we observe a negative gross relation between the Z-score and systemic risk, while bank profitability and systemic risk display an insignificant positive correlation.

Table 3 presents partial correlations between the three aforementioned dependent variables. The partial correlation between risk-taking and profitability in column 1 is consistent with the corresponding gross correlation in Table 2. However, once we take into account control factors, the coefficient between systemic risk and bank risk-taking turns positive, as shown in column 3 of Table 3, indicating that higher risk-taking (lower Z-score) is associated with lower systemic risk. Finally, the same table reports that higher bank profitability is now associated with lower systemic risk (column 2). The results suggest that gross relations can obscure the picture of interlinkages. The findings in the subsequent sections help us to build on these correlations and establish a distinct channel that highlights the distributional effects of QE on risk-taking, profitability, and systemic risk.

**Table 3. Baseline Partial Correlations**

	Z-score	SES	
	(1)	(2)	(3)
Net Interest Income	-0.091* (0.050)	-0.052* (0.027)	
Z-score			0.023** (0.009)
Size	0.082 (0.050)	0.055** (0.028)	0.003 (0.006)
Liquidity	-1.554*** (0.091)	0.316*** (0.058)	0.466*** (0.081)
Tier 1 Capital Ratio	0.023*** (0.005)	0.005** (0.003)	0.001 (0.004)
Leverage Ratio	0.065*** (0.007)	-0.018*** (0.004)	-0.022*** (0.006)
Observations	4,461	4,981	4,473
R-squared	0.919	0.204	0.198
Bank Fixed Effects	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes

**Note:** The dependent variable in column 1 is the logarithm of Z-score, while in columns 2 and 3 it is the systemic expected shortfall. The null hypothesis of cross-sectional independence in Pesaran's (2021) test can be rejected for regression residuals at conventional significance levels. However, the average and average absolute cross-sectional correlations are relatively low, standing approximately at 0.1 and 0.3 for risk-taking (Z-scores) and approximately 0.04 and 0.2 (columns 2 and 3) for systemic risk (SES). According to Pesaran (2021), in finite samples, the assumption of cross-sectional independence is appropriate when cross-sectional correlations are low. Constant terms included but not reported. Robust standard errors in parentheses. \*\*\*, \*\*, and \* represent significance at 1 percent, 5 percent, and 10 percent, respectively.

## 4.2 Benchmark QE Regressions

### 4.2.1 Bank Risk-Taking

Table 4 presents the main regression results for the impact of QE on individual bank risk-taking. Corresponding to different definitions of the treatment variable, columns 2, 4, and 6 present results using

Table 4. The Impact of QE on Bank Risk-Taking

	Z-score					
	(1)	(2)	(3)	(4)	(5)	(6)
$QE1_t \times Treat_i^Q$	0.010 (0.018)	0.022 (0.017)				
$QE2_t \times Treat_i^Q$	0.008 (0.025)	-0.013 (0.023)				
$QE3_t \times Treat_i^Q$	-0.043** (0.017)	-0.048*** (0.017)				
$QE1_t \times Treat_i^D$			-0.026 (0.027)	-0.011 (0.025)		
$QE2_t \times Treat_i^D$			0.008 (0.038)	-0.040 (0.035)		
$QE3_t \times Treat_i^D$			-0.054** (0.026)	-0.125*** (0.026)		
$QE1_t \times \left(\frac{MBS}{TotalAssets}\right)_i$					0.074 (0.085)	0.104 (0.084)
$QE2_t \times \left(\frac{MBS}{TotalAssets}\right)_i$					0.098 (0.117)	0.050 (0.115)
$QE3_t \times \left(\frac{MBS}{TotalAssets}\right)_i$					-0.220*** (0.081)	-0.263*** (0.087)

(continued)

Table 4. (Continued)

	Z-score					
	(1)	(2)	(3)	(4)	(5)	(6)
Observations	11,391	10,128	4,591	4,082	20,876	19,724
R-squared	0.077	0.114	0.067	0.102	0.122	0.127
Bank-Level Controls	No	Yes	No	Yes	No	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

**Note:** The dependent variable in columns 1–6 is the logarithm of Z-scores.  $Treat_i^Q$  takes the value 1 for banks in the top quartile (top 25 percent) of the MBS-to-total-assets distribution, while 0 for banks in the bottom quartile (bottom 25 percent) of the distribution.  $Treat_i^D$  takes the value 1 for banks in the top decile (top 10 percent) of the MBS-to-total-assets ratio, and 0 for banks in the bottom decile (bottom 10 percent) of the distribution.  $\left(\frac{MBS}{TotalAssets}\right)_i$  is the ratio of MBS to total assets in 2007:Q4.  $QE1_t$ ,  $QE2_t$ , and  $QE3_t$  are dummy variables corresponding to the respective QE waves, where the dummy takes the value 1 during the QE episode and 0 otherwise. Control variables include bank size, liquidity, tier 1 capital ratio, loans-to-assets ratio, and leverage ratio. All control variables are taken as lagged. Including interactions between controls and the treatment variables does not alter results significantly. The null hypothesis of cross-sectional independence in Pesaran’s (2021) test can be rejected for regression residuals at conventional significance levels. However, the average and average absolute cross-sectional correlations are relatively low, each standing approximately at 0.1 across regressions. According to Pesaran (2021), in finite samples, the assumption of cross-sectional independence is appropriate when cross-sectional correlations are low. Constant terms included but not reported. Robust standard errors in parentheses. \*\*\*, \*\*, and \* represent significance at 1 percent, 5 percent, and 10 percent, respectively.

the main specification model that includes control variables. Meanwhile, columns 1, 3, and 5 exclude all bank controls. The regression employs the Z-score as the dependent variable, which indicates the inverse probability of insolvency. A lower Z-score represents higher risk-taking by banks.

The results suggest that banks with larger MBS holdings increase their relative risk-taking capacity during the third round of QE (QE3). This is indicated by the negative and statistically significant coefficient on the interaction term between treated banks and QE3 across most specifications. In particular, banks in the top quartile and decile, respectively, of the MBS-to-total-assets ratio show an increase in risk-taking by 4.8 percent (column 2) and 12.5 percent (column 4), respectively. Additionally, we employ the treatment status of banks based on the continuous measure of MBS to total assets. It can be inferred from the results shown in column 6 that banks with higher MBS to assets increased their risk-taking by approximately 26.3 percent.<sup>19</sup>

Our results complement the findings of Luck and Zimmermann (2020) that show higher loan supply by the treated banks during QE3, a possible channel for increased riskiness as shown in Kurtzman, Luck, and Zimmermann (2022).<sup>20</sup> Our results are also consistent with the previous literature on the impact of conventional monetary policy on bank risk-taking, including Gambacorta (2009), Altunbas, Gambacorta, and Marques-Ibanez (2010), and Delis and Kouretas (2011) among others, that confirms the presence of a risk-taking channel during episodes of expansionary monetary policy.

Table 4 further indicates statistically insignificant effects for bank risk-taking during QE1. The direction of the coefficients and their economic significance is opposite to the evidence obtained for QE3.<sup>21</sup> Ignoring statistical significance, the results overall suggest that bank

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<sup>19</sup>More accurate effects can be obtained from  $(e^\theta - 1) \times 100$ .

<sup>20</sup>Although Kurtzman, Luck, and Zimmermann (2022) highlight the negative relation between QE and bank lending standards, which measures the quality of loans rather than quantity, their findings address the fact that banks increase their risk-taking due to both lower lending standards and greater availability of credit.

<sup>21</sup>Since Z-score is a measure of bank stability, note that a positive coefficient on the interaction term would imply high stability and low risk-taking by treated banks during QE1.

risk-taking decreased in the initial phases of QE. Taking statistical significance into account, the interpretation is that banks refrained from additional risk-taking despite an increase in liquidity, implying a decrease in relative risk-taking when compared to the amount of liquidity available. Our understanding of this result is based on the study of Kapoor and Peia (2021), which yields no evidence of loan growth during QE1. Since studies such as that of Kurtzman, Luck, and Zimmermann (2022) associate riskiness with bank lending, an increase in riskiness during QE1 was an unlikely result. Moreover, the QE3 program was larger in scale as compared to QE1, implying that banks, as a response to the economic crisis of 2007–08, used the QE program in the first round to reduce their riskiness.<sup>22</sup> By the time QE3 was implemented, banks were better prepared to increase their appetite for risk through higher lending. Our results reveal that it was only after QE3, as opposed to QE1, that banks' portfolios reflected this pattern. This is consistent with Luck and Zimmermann (2020), who investigate the employment effects of disparate QE rounds and find a substantial difference between treated and control banks after QE3 only.

The regression controls for time-variant bank characteristics include bank size, tier 1 capital ratio, liquidity, leverage ratio, and loans-to-asset ratio. The overall findings are relatively robust across all specifications. We note that the time-invariant heterogeneity between treated and control groups is addressed via bank fixed effects, while the demand-side conditions that affect borrower riskiness are controlled by employing year-quarter and state fixed effects.

#### *4.2.2 Bank Profitability*

The results in Table 5 investigate the impact of QE on bank profitability, measured by the logarithm of net interest income which reflects the capability of a bank to generate profits from its asset management functions.<sup>23</sup> As before, the main variables of interest

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<sup>22</sup>This is somewhat implied by the statistically insignificant positive coefficients on the interaction terms in columns 1–2 and 5–6 for QE1.

<sup>23</sup>We lose only nine observations by taking the logarithm of net interest income, which is a minuscule amount given that we have over 30,000 observations in the sample. Using the non-log variable yields similar results qualitatively.

Table 5. The Impact of QE on Bank Profitability

	Net Interest Income					
	(1)	(2)	(3)	(4)	(5)	(6)
$QE1_t \times Treat_i^Q$	0.051*** (0.014)	0.061*** (0.011)				
$QE2_t \times Treat_i^Q$	0.045** (0.019)	0.050*** (0.013)				
$QE3_t \times Treat_i^Q$	0.076** (0.032)	0.038** (0.017)				
$QE1_t \times Treat_i^D$			0.082*** (0.015)	0.074*** (0.009)		
$QE2_t \times Treat_i^D$			0.058*** (0.021)	0.048*** (0.013)		
$QE3_t \times Treat_i^D$			0.078*** (0.014)	0.019* (0.010)		
$QE1_t \times \left(\frac{MBS}{TotalAssets}\right)_i$					0.340*** (0.068)	0.354*** (0.056)
$QE2_t \times \left(\frac{MBS}{TotalAssets}\right)_i$					0.238** (0.100)	0.271*** (0.072)
$QE3_t \times \left(\frac{MBS}{TotalAssets}\right)_i$					0.467*** (0.174)	0.253* (0.136)

(continued)

Table 5. (Continued)

	Net Interest Income					
	(1)	(2)	(3)	(4)	(5)	(6)
Observations	12,786	11,040	5,148	4,445	24,997	21,526
R-squared	0.879	0.945	0.889	0.956	0.881	0.946
Bank-Level Controls	No	Yes	No	Yes	No	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

**Note:** The dependent variable in columns 1–6 is logarithm of net interest income.  $Treat_i^Q$  takes the value 1 for banks in the top quartile (top 25 percent) of the MBS-to-total-assets distribution, while 0 for banks in the bottom quartile (bottom 25 percent) of the distribution.  $Treat_i^D$  takes the value 1 for banks in the top decile (top 10 percent) of the MBS-to-total-assets ratio, and 0 for banks in the bottom decile (bottom 10 percent) of the distribution.  $\left(\frac{MBS}{TotalAssets}\right)_i$  is the ratio of MBS to total assets in 2007:Q4.  $QE1_t$ ,  $QE2_t$ , and  $QE3_t$  are dummy variables corresponding to the respective QE waves, where the dummy takes the value 1 during the QE episode and 0 otherwise. Control variables include bank size, liquidity, tier 1 capital ratio, and leverage ratio. All control variables are taken as lagged. Including interactions between controls and the treatment variables does not alter results significantly. The null hypothesis of cross-sectional independence in Pesaran’s (2021) test can be rejected for regression residuals at conventional significance levels. However, the average and average absolute cross-sectional correlations are relatively low, each standing approximately at 0.1 across regressions. According to Pesaran (2021), in finite samples, the assumption of cross-sectional independence is appropriate when cross-sectional correlations are low. Constant terms included but not reported. Robust standard errors in parentheses. \*\*\*, \*\*, and \* represent significance at 1 percent, 5 percent, and 10 percent, respectively.

are the interaction terms between the QE time dummies and banks' treatment status.

Our results overall suggest that treated banks generated larger profits during all episodes of QE. Specifically, in our sample of QE3, banks above the 75th percentile of the MBS-to-total-assets distribution increase their net interest income by about 3.8 percent (column 2) relative to banks below the 25th percentile of the MBS distribution. The results hold for different treatment definitions, i.e., based on the 10th and 90th percentiles of the MBS holdings (columns 3 and 4) and the continuous measure (columns 5 and 6). Our findings are consistent with the previous literature, including Flannery (1981), Bourke (1989), and Saunders and Schumacher (2000), that provides evidence of a positive association between monetary policy and bank profitability.

#### 4.2.3 Systemic Risk

Our main empirical specification uses the Acharya et al. (2017) systemic expected shortfall index (*SES*) for bank  $i$  in year-quarter  $t$  relative to year-quarter  $t-1$  as the dependent variable. The results are presented in Table 6. Again, we employ three treatment variables that classify banks based on quartiles, deciles, and the continuous measure of MBS to total assets.

Our main variable of interest, the interaction term  $QE3_t \times Treat_i$ , is negative and statistically significant across all definitions of the treatment variable, suggesting that banks with large MBS-to-total-assets holdings reduced their contribution to systemic risk during the third round of quantitative easing. The findings imply that QE had a positive effect on banking-sector stability. Our results are consistent with those of Berger, Roman, and Sedunov (2017), who report a positive impact of QE on the financial sector after the implementation of TARP.

Together, the results in Tables 4, 5, and 6 suggest that banks carrying higher MBS-to-total-assets ratios were characterized by higher levels of risk-taking and corresponding profitability in QE3, with evidence of higher profits in QE1 and QE2 as well. Finally, since the QE programs were largely unanticipated, especially the third round, banks that held more MBS had a prompt recovery and reduced their contribution to systemic risk.

Table 6. The Impact of QE on Systemic Risk

	Systemic Expected Shortfall					
	(1)	(2)	(3)	(4)	(5)	(6)
$QE1_t \times Treat_i^Q$	-0.014 (0.029)	-0.015 (0.029)				
$QE2_t \times Treat_i^Q$	-0.013 (0.046)	-0.011 (0.046)				
$QE3_t \times Treat_i^Q$	-0.092** (0.039)	-0.125*** (0.041)				
$QE1_t \times Treat_i^D$			-0.027 (0.055)	-0.027 (0.055)		
$QE2_t \times Treat_i^D$			-0.028 (0.084)	-0.015 (0.085)		
$QE3_t \times Treat_i^D$			-0.141* (0.080)	-0.134* (0.084)		
$QE1_t \times \left( \frac{MBS}{TotalAssets} \right)_i$					-0.100 (0.139)	-0.105 (0.136)
$QE2_t \times \left( \frac{MBS}{TotalAssets} \right)_i$					-0.056 (0.217)	-0.037 (0.213)
$QE3_t \times \left( \frac{MBS}{TotalAssets} \right)_i$					-0.363* (0.191)	-0.494** (0.192)

*(continued)*

Table 6. (Continued)

	Systemic Expected Shortfall					
	(1)	(2)	(3)	(4)	(5)	(6)
Observations	1,958	1,919	786	781	3,813	3,736
R-squared	0.193	0.175	0.125	0.128	0.209	0.217
Bank-Level Controls	No	Yes	No	Yes	No	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

**Note:** The dependent variable in columns 1–6 is the change in  $SES_t$ .  $Treat_i^Q$  takes the value 1 for banks in the top quartile (top 25 percent) of the MBS-to-total-assets distribution, while 0 for banks in the bottom quartile (bottom 25 percent) of the distribution.  $Treat_i^D$  takes the value 1 for banks in the top decile (top 10 percent) of the MBS-to-total-assets ratio, and 0 for banks in the bottom decile (bottom 10 percent) of the distribution.  $\left(\frac{MBS}{TotalAssets}\right)_i$  is the ratio of MBS to total assets in 2007:Q4.  $QE1_t$ ,  $QE2_t$ , and  $QE3_t$  are dummy variables corresponding to the respective QE waves, where the dummy takes the value 1 during the QE episode and 0 otherwise. Control variables include bank size, liquidity, tier 1 capital ratio, deposit ratio, and leverage ratio. All control variables are taken as lagged. Including interactions between controls and the treatment variables does not alter results significantly. The null hypothesis of cross-sectional independence in Pesaran’s (2021) test can be rejected for regression residuals at conventional significance levels. However, the average and average absolute cross-sectional correlations are relatively low, each standing approximately at 0.06 across regressions. According to Pesaran (2021), in finite samples, the assumption of cross-sectional independence is appropriate when cross-sectional correlations are low. Constant terms included but not reported. Robust standard errors in parentheses. \*\*\*, \*\*, and \* represent significance at 1 percent, 5 percent, and 10 percent, respectively.

### 4.3 *Systems Approach*

We also estimate our three specifications as a system of pooled equations via the seemingly unrelated regressions (SUR) model that employs the feasible generalized least squares (FGLS) estimator. A second system is estimated using the general method of moments (GMM) estimator. The system approach is adopted in order to account for potential cross-equation correlations in residuals and improve efficiency.<sup>24</sup> Possible endogeneity issues are further addressed via lags of variables as instruments in the GMM case. As is evident from Tables 7 and 8, the system estimates are consistent with the individual regression estimates in Tables 4–6.

### 4.4 *Too Big to Fail and Systemic Risk*

Following the GFC, the authorities attempted to prevent the failure of a few systemically important financial institutions (SIFIs) in order to avoid the risks posed to the overall financial system and broader economy. Failure of SIFIs, although uncommon, can have negative consequences for the entire financial system. These entities are often referred to as “too big to fail” (TBTF) due to their interconnected, sufficiently large, complex operations.

In the face of systemic failure, large financial institutions such as TBTFs accept government support, more commonly in the form of bailouts, that assists them in the recovery process (Cetorelli and Traina 2018). Accordingly, we focus on the impact of QE on systemic risk contributions by TBTF banks. This analysis draws motivation from the growing need to identify and monitor TBTFs, so that timely steps can be taken in order to avert events of economic distress associated with the failure of these systemically important banks.

We follow Zhou (2010) and identify the TBTF banks in our data.<sup>25</sup> To investigate the impact of QE on systemic risk

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<sup>24</sup>We analyze frameworks with control factors that differ across equations.

<sup>25</sup>We are able to label 16 banks as TBTF. TBTF banks must satisfy the following selection criteria: (i) the financial institutions should be classified as “banks,” (ii) they should be traded on the NYSE, and (iii) they should be active from the beginning of 1987 until 2009.

**Table 7. The Impact of QE on Bank Risk-Taking, Profitability, and Systemic Risk: Seemingly Unrelated Regressions**

	Z-score	NII	SES
	(1)	(2)	(3)
$QE1_t \times Treat_i^Q$	-0.044 (0.122)	0.084 (0.067)	-0.324 (0.616)
$QE2_t \times Treat_i^Q$	0.003 (0.198)	0.069 (0.109)	-0.056 (0.051)
$QE3_t \times Treat_i^Q$	-0.529*** (0.140)	0.159** (0.077)	-1.56** (0.706)
Observations	1,928	1,928	1,928
R-squared	0.816	0.830	0.107
$QE_t$	Yes	Yes	Yes
Treatment Variable	Yes	Yes	Yes

**Note:** Pooled regressions employed. The dependent variable in column 1 is the logarithm of Z-score, in column 2 is the logarithm of net interest income (NII), and in column 3 is the systemic expected shortfall (SES).  $Treat_i^Q$  takes the value 1 for banks in the top quartile (top 25 percent) of the MBS-to-total-assets distribution, while 0 for banks in the bottom quartile (bottom 25 percent) of the distribution.  $QE1_t$ ,  $QE2_t$ , and  $QE3_t$  are dummy variables corresponding to the respective QE waves, where the dummy takes the value 1 during the QE episode and 0 otherwise. Control variables include bank size, liquidity, tier 1 capital ratio, deposit ratio, and leverage ratio. All control variables are taken as lagged. Including interactions between controls and the treatment variables does not alter results significantly. The null hypothesis of cross-sectional independence in Pesaran’s (2021) test can be rejected for regression residuals at conventional significance levels. However, the average and average absolute cross-sectional correlations are relatively low, standing approximately at 0.06 and 0.06 for Z-scores; 0.04 and 0.05 for NII; and 0.03 and 0.05 for SES. According to Pesaran (2021), in finite samples, the assumption of cross-sectional independence is appropriate when cross-sectional correlations are low. Constant terms included but not reported. Robust standard errors in parentheses. \*\*\*, \*\*, and \* represent significance at 1 percent, 5 percent, and 10 percent, respectively.

contributions by TBTF banks, we estimate the following regression model:

$$\begin{aligned}
 Y_{i,t} = & \alpha_i + \beta_t + \rho_{i,t} + \gamma_1'QE_t + \gamma_2TBTF_i + \theta'TBTF_i \\
 & \times QE_t + \delta'X_{i,t-1} + \epsilon_{i,t},
 \end{aligned}
 \tag{6}$$

**Table 8. The Impact of QE on Bank Risk-Taking, Profitability, and Systemic Risk: System GMM**

	Z-score	NII	SES
	(1)	(2)	(3)
$QE1_t \times Treat_t^Q$	-0.097 (0.122)	0.171** (0.083)	-0.067* (0.039)
$QE2_t \times Treat_t^Q$	-0.037 (0.133)	0.256** (0.118)	-0.160** (0.065)
$QE3_t \times Treat_t^Q$	-0.273* (0.142)	0.567*** (0.191)	-0.816*** (0.276)
Observations	1,691	1,691	1,691
$QE_t$	Yes	Yes	Yes
Treatment Variable	Yes	Yes	Yes

**Note:** Pooled regressions employed. The dependent variable in column 1 is the logarithm of Z-score, in column 2 is the logarithm of net interest income (NII), and in column 3 is the systemic expected shortfall (SES).  $Treat_t^Q$  takes the value 1 for banks in the top quartile (top 25 percent) of the MBS-to-total-assets distribution, while 0 for banks in the bottom quartile (bottom 25 percent) of the distribution.  $QE1_t$ ,  $QE2_t$ , and  $QE3_t$  are dummy variables corresponding to the respective QE waves, where the dummy takes the value 1 during the QE episode and 0 otherwise. Control variables include bank size, liquidity, tier 1 capital ratio, deposit ratio, and leverage ratio. All control variables are taken as lagged. Including interactions between controls and the treatment variables does not alter results significantly. The null hypothesis of cross-sectional independence in Pesaran's (2021) test can be rejected for regression residuals at conventional significance levels. However, the average and average absolute cross-sectional correlations are relatively low, standing approximately at 0.00 and 0.00 for Z-scores; 0.05 and 0.06 for NII; and 0.00 and 0.00 for SES. According to Pesaran (2021), in finite samples, the assumption of cross-sectional independence is appropriate when cross-sectional correlations are low. Constant terms included but not reported. Robust standard errors in parentheses. \*\*\*, \*\*, and \* represent significance at 1 percent, 5 percent, and 10 percent, respectively.

where  $TBTF_i$  is a dummy variable that takes the value of 1 if a bank is identified as “too big to fail” and 0 otherwise. All other variables carry the same interpretation as in Equation (5) and the results are presented in Table 9.

TBTF banks are prone to moral hazard. If TBTF firms believe that the government will protect them during periods of distress, they have less incentive to monitor their financial operations (Dam

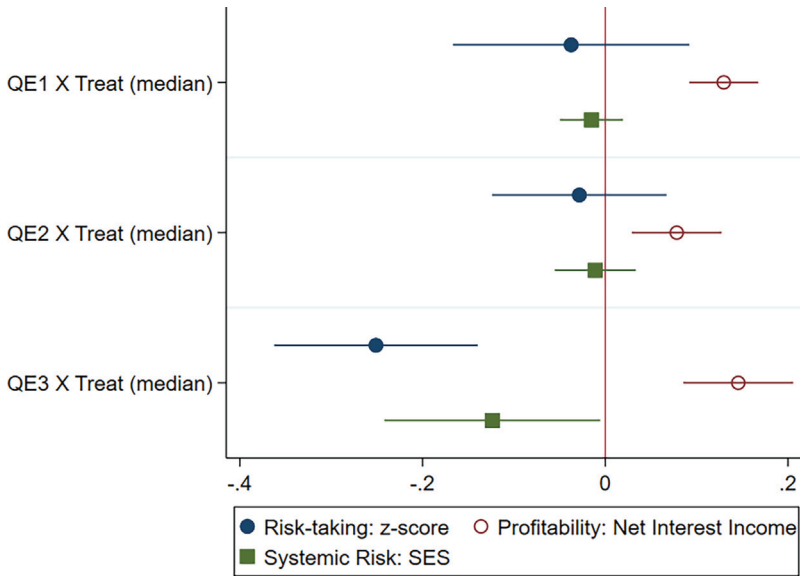
**Table 9. The Impact of QE on Systemic Risk for Too-Big-to-Fail Banks**

	Systemic Expected Shortfall	
	(1)	(2)
$QE1_t \times TBTF_i$	-0.008 (0.015)	-0.006 (0.014)
$QE2_t \times TBTF_i$	-0.080* (0.043)	-0.081* (0.045)
$QE3_t \times TBTF_i$	-0.138** (0.061)	-0.147** (0.064)
Observations	4,548	4,355
R-squared	0.235	0.220
Number of Banks	277	246
$QE_t$	Yes	Yes
Bank-Level Controls	No	Yes
Year-Quarter Fixed Effects	Yes	Yes
Bank Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes

**Note:** The dependent variable is the growth rate of SES.  $TBTF_i$  is a dummy that takes the value 1 for banks that are identified as systemically important financial institutions (SIFIs), or too big to fail (TBTF), by the Financial Stability Board and 0 otherwise.  $QE1_t$ ,  $QE2_t$ , and  $QE3_t$  are dummy variables corresponding to the respective QE waves, where the dummy takes the value 1 during the QE episode and 0 otherwise. Control variables include bank size, liquidity, tier 1 capital ratio, deposit ratio, and leverage ratio. All control variables are taken as lagged. Including interactions between controls and the treatment variables does not alter results significantly. The null hypothesis of cross-sectional independence in Pesaran’s (2021) test can be rejected for regression residuals at conventional significance levels. However, the average and average absolute cross-sectional correlations are relatively low, standing approximately at 0.04 and 0.2. According to Pesaran (2021), in finite samples, the assumption of cross-sectional independence is appropriate when cross-sectional correlations are low. Constant terms included but not reported. Robust standard errors in parentheses. \*\*\*, \*\*, and \* represent significance at 1 percent, 5 percent, and 10 percent, respectively.

and Koetter 2012). With regards to the effectiveness of QE in reducing the contribution of TBTF banks to systemic risk, our results show that the policy had stabilizing effects. Moreover, the coefficient on the interaction term  $QE3_t \times TBTF_i$  is -0.147 (column 2),

**Figure 3. Robustness Test: Treatment Variable Based on Median**



**Note:** The figure shows coefficient estimates where dependent variables are the logarithm of Z-score, the logarithm of net interest income, and the change in systemic expected shortfall. The regression uses an alternative treatment definition, with the dummy now equal to 1 if banks have an above-the-median ratio of MBS to total assets in 2007:Q4, and 0 if the ratio is below the median. Control variables include bank size, liquidity, tier 1 capital ratio, deposit ratio, and leverage ratio. All control variables are taken as lagged. The estimation includes bank fixed effects, year-quarter fixed effects, state effects, and lagged values of bank-level controls.

which is similar to the size of the effect obtained for the full sample of banks as discussed in the previous sections.

#### 4.5 Other Robustness Checks

We perform a series of further robustness checks on our main results. First, we introduce a new treatment variable based on the median ratio of MBS holdings to total assets. This dummy variable takes the value of 1 if a bank is in the top half of the distribution of MBS to total assets in 2007:Q4 and 0 if it lies in the bottom half of the distribution. Figure 3 shows a plot of estimated coefficients  $\theta$

from Equation (5). Similar to the findings observed so far, it confirms that treated banks had significantly increased their capacity of risk-taking and profitability, and decreased their contribution to systemic risk during QE3.

Second, we use a bank's MBS exposure relative to securities, changing the specification to

$$Y_{i,t} = \alpha_i + \beta_t + \rho_{i,t} + \gamma'_1 QE_t + \gamma_2 \left( \frac{MBS}{Securities} \right)_i + \theta' \left( \frac{MBS}{Securities} \right)_i \times QE_t + \delta' X_{i,t-1} + \epsilon_{i,t}. \quad (7)$$

This measure has been employed in earlier studies, including that of Kurtzman, Luck, and Zimmermann (2022), and captures the treatment status of banks in relation to only the total securities, thus reducing any noise in the treatment specification when compared to the use of total assets in the denominator of the ratio. The results are presented in Table 10 and are qualitatively similar to the ones obtained in our main specifications. We still find stronger support for a differential increase in risk-taking and profitability, and a simultaneous decrease in systemic risk during QE3.

Third, we employ alternative measures of our dependent variables. We capture bank riskiness with the ratio of risk assets to total assets, while we use return on assets as a proxy for bank profitability. Systemic risk is captured by *SRISK*, which measures the amount of capital a bank would require for the maintenance of a given capital-asset ratio during periods of distress. *SRISK* is a function of bank size, which is captured by equity, leverage, and long-run *MES*. Following Brownlees and Engle (2017), *SRISK* is defined as

$$\begin{aligned} SRISK_{i,t} &= E_t[CapitalShortfall_{i,t+1}|Crisis] \\ &= E_t[k(Debt_{i,t+1} + Equity_{i,t+1}) - Equity_{i,t+1}|Crisis] \\ &= kDebt_{i,t} - (1-k)(1-LRMES_{i,t})Equity_{i,t}, \end{aligned} \quad (8)$$

where  $Debt_{i,t}$  is the book value of debt,  $Equity_{i,t}$  is the market value of equity, and  $k$  is the prudential capital fraction, i.e., level of book equity relative to assets, and is taken as 8 percent in line

**Table 10. The Impact of QE on Bank Risk-Taking, Profitability, and Systemic Risk: Varying Treatment Definition**

	Z-score		Net Interest Income		SES	
	(1)	(2)	(3)	(4)	(5)	(6)
$QE1_t \times Treat/Sec_t^Q$	0.005 (0.018)	0.014 (0.017)	0.038*** (0.008)	0.043*** (0.006)	-0.015 (0.022)	-0.016 (0.021)
$QE2_t \times Treat/Sec_t^Q$	-0.038* (0.022)	-0.031 (0.019)	0.041*** (0.011)	0.050*** (0.008)	0.001 (0.035)	-0.000 (0.034)
$QE3_t \times Treat/Sec_t^Q$	-0.095*** (0.020)	-0.071*** (0.021)	0.068*** (0.011)	0.043*** (0.008)	-0.065*** (0.030)	-0.077*** (0.031)
Observations	10,757	9,607	12,109	10,459	3,687	3,613
R-squared	0.646	0.665	0.984	0.993	0.229	0.236
Bank-Level Controls	No	Yes	No	Yes	No	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

**Note:** The dependent variable in columns 1 and 2 is the logarithm of Z-score, in columns 3 and 4 is the logarithm of net interest income, and in columns 5 and 6 is the systemic expected shortfall (SES).  $Treat/Sec_t^Q$  takes the value 1 for banks in the top quartile (top 25 percent) of the MBS-to-securities distribution, while 0 for banks in the bottom quartile (bottom 25 percent) of the distribution.  $QE1_t$ ,  $QE2_t$ , and  $QE3_t$  are dummy variables corresponding to the respective QE waves, where the dummy takes the value 1 during the QE episode and 0 otherwise. Control variables include bank size, liquidity, tier 1 capital ratio, deposit ratio, and leverage ratio. All control variables are taken as lagged. Including interactions between controls and the treatment variables does not alter results significantly. The null hypothesis of cross-sectional independence in Pesaran's (2021) test can be rejected for regression residuals at conventional significance levels. However, the average and average absolute cross-sectional correlations are relatively low, standing approximately at 0.07 and 0.07 for Z-scores; 0.07 and 0.07 for NI; and 0.03 and 0.05 for SES. According to Pesaran (2021), in finite samples, the assumption of cross-sectional independence is appropriate when cross-sectional correlations are low. Constant terms included but not reported. Robust standard errors in parentheses. \*\*\*, \*\*, and \* represent significance at 1 percent, 5 percent, and 10 percent, respectively.

with Brownlees and Engle (2017).<sup>26</sup> Finally,  $LRMES_{i,t}$  is the long-run MES for bank  $i$  at time  $t$ , which is the average of returns on bank equity in the crisis period. Acharya, Engle, and Richardson (2012) approximate  $LRMES_{i,t}$  as  $1 - \exp\{-18 \times MES_{i,t}\}$ . Table 11 shows that the coefficient on the interaction term between QE3 and the treatment variable remains significant and of the expected sign across dependent variables.

## 5. Conclusions

Bank risk-taking has gained much attention in recent times, as it is widely viewed as one of the outlets of unconventional monetary policy. The risk-taking channel also explains the reasons for the severity of the Global Financial Crisis. While individual risk-taking has been discussed in the literature, the impact on systemic risk is still less explored. Our paper explores the distributional effects of QE by examining whether banks that benefited more from the Fed's three rounds of QE also lowered their contribution to systemic risk.

We investigate whether QE-exposed banks increased their risk-taking capacity in order to achieve higher incomes and maximize profits. Since high incomes reflect the capability of a bank to generate higher profits from its asset management functions, we expect higher-income banks to be more stable. Furthermore, profitable banks have the necessary cushion to absorb losses, which reduces the probability of financial distress or failure.

Our results suggest that banks were encouraged to increase their risk-taking capacity and profitability due to the excess liquidity created by loose monetary policy. At the same time, banks reduced their contribution to systemic risk, suggesting that the implementation of QE had an overall positive effect on banking-sector stability. This is an important finding, as it shows that QE not only encouraged banks to take on higher risk, which led to increased availability of credit and liquidity, but also assisted in pulling the banking system out

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<sup>26</sup>The capital shortfall can be interpreted as the negative of working capital, i.e., the institution has a capital surplus when the capital shortfall is negative and suffers distress when capital shortfall is positive. Equation (8) assumes that debt cannot be renegotiated in the case of a crisis or systemic event.

**Table 11. Varying Measures of Dependent Variable**

	Risk/TA	ROA	SRISK
	(1)	(2)	(3)
$QE1_t \times Treat_i^Q$	-0.005*** (0.002)	0.001*** (0.000)	0.174 (0.346)
$QE2_t \times Treat_i^Q$	0.010*** (0.002)	0.001*** (0.000)	-0.782 (0.550)
$QE3_t \times Treat_i^Q$	0.013*** (0.002)	0.001*** (0.000)	-0.684* (0.405)
Observations	11,040	10,585	1,940
R-squared	0.758	0.654	0.903
Bank-Level Controls	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes

**Note:** The dependent variable in column 1 is risk assets scaled by total assets, in column 2 is the return on assets, and in column 3 is *SRISK* scaled by bank equity.  $Treat_i^Q$  takes the value 1 for banks in the top quartile (top 25 percent) of the MBS-to-total-assets distribution, while 0 for banks in the bottom quartile (bottom 25 percent) of the distribution.  $QE1_t$ ,  $QE2_t$ , and  $QE3_t$  are dummy variables corresponding to the respective QE waves, where the dummy takes the value 1 during the QE episode and 0 otherwise. Control variables include bank size, liquidity, tier 1 capital ratio, and leverage ratio. All control variables are taken as lagged. Including interactions between controls and the treatment variables does not alter results significantly. The null hypothesis of cross-sectional independence in Pesaran's (2021) test can be rejected for regression residuals at conventional significance levels. However, the average and average absolute cross-sectional correlations are relatively low, standing approximately at 0.07 and 0.07 for risk assets to total assets; 0.09 and 0.09 for ROA; and 0.04 and 0.05 for *SRISK*. According to Pesaran (2021), in finite samples, the assumption of cross-sectional independence is appropriate when cross-sectional correlations are low. Constant terms included but not reported. Robust standard errors in parentheses. \*\*\*, \*\*, and \* represent significance at 1 percent, 5 percent, and 10 percent, respectively.

of recession. Overall, our paper illustrates implications for individual banks and the financial system when assessing the distributional impact of QE.

We contribute to the literature by providing one of the first studies to investigate the impact of quantitative easing on the contribution of banks to systemic risk. Moreover, we investigate a potential mechanism that explains how QE encouraged banks to take up more risk in search of higher profits, thus making the banking sector more stable.

Appendix. Variables Employed: Construction and Corresponding Definitions

Table A.1. Variable Details

Variable Name	Definition	Data Sources
Securities Holdings	Held-to-maturity securities (BHCK1754) + available-for-sale securities (BHCK1773)	FR-Y9C
Treasury Securities	Trading Assets: Treasury Securities (BHCK3531)	FR-Y9C
Bank Size	Log of total assets (BHCK2170)	FR-Y9C
Equity Ratio	Total equity capital (BHCK3210) divided by total assets (BHCK2170)	FR-Y9C
Deposit Ratio	Non-interest-bearing deposits in domestic offices (BHDM6631) + interest-bearing deposits in domestic offices (BHDM6636) + non-interest-bearing deposits in foreign offices (BHFN6631) divided by total assets (BHCK2170)	FR-Y9C
Liquidity	Cash and balances due from depository institutions: non-interest-bearing balances and currency and coin (BHCK0081) + interest-bearing balances in U.S. offices (BHCK0395) + interest-bearing balances in foreign offices, Edge and Agreement subsidiaries, and IBFs (BHCK0397) divided by total assets (BHCK2170)	FR-Y9C
Total Lending	Total loans (BHCK2122) divided by total assets (BHCK2170)	FR-Y9C
Net Interest Income	Logarithm of net interest income (BHCK4074)	FR-Y9C
Return on Assets	Net income (BHCK4340) divided by average total assets (BHCT3368)	FR-Y9C
Z-score	Sum of ROA and equity ratio divided by standard deviation of asset returns	FR-Y9C
Risk Assets	Total assets (BHCK2170) – cash and balances due from depository institutions (BHCK0081 + BHCK0395 + BHCK0397) – federal funds sold (BHDMB987) – securities purchased under agreement to resell (BHCKB989) divided by total assets (BHCK2170)	FR-Y9C
SES	Propensity of a bank to be undercapitalized when the entire banking system is undercapitalized	CRSP and FR-Y9C
SRISK	Amount of capital that is required by a financial institution during periods of crisis	CRSP and FR-Y9C

**Note:** The table presents data sources and method of construction of variables used in analysis. FR-Y9C refers to balance sheet information of all BHCs from the Federal Reserve Bank of Chicago. CRSP refers to market data in the Center for Research in Security Prices database.

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