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

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

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Abstract

In the aftermath of the sub-prime mortgage bubble, the Federal Reserve implemented large scale asset purchase (LSAP) programmes 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 that, particularly during the third round of QE, banks that were more exposed to the unconventional monetary policy 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.

Keywords: large-scale asset purchases, quantitative easing, bank risk-taking, systemic risk, expected shortfall

JEL codes: E52, E58, G21

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1. Introduction

Traditionally, central banks employ short-term interest rates to stabilize inflation and economic fluctuations. The period preceding the Global Financial Crisis (GFC) of 2007-2008 featured low monetary policy rates that led to a deterioration of bank lending standards and subsequent increases in risk-taking (Dell'Ariccia et al. 2014, Bernanke et al. 2020). The persistently low real interest rate environment fuelled 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 et al. 2010, Paligorova & Santos 2017). Hence, banks are considered to have played a significant role in the build-up and spread of systemic risk (Nijskens & 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 responded to the zero lower bound and subsequent worsening of the economic crisis by embarking on large-scale asset purchase programmes, often referred to as quantitative easing (QE), with an intention to provide additional monetary stimulus, restore stability, and reduce 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.[1] 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 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,[2] 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. Recent evidence suggests that bailouts can reduce systemic risk either through a higher charter value

[1]While quantitative easing has shown to boost lending and liquidity in the banking sector (Rodnyansky & Darmouni 2017, Chakraborty et al. 2020, Luck & Zimmermann 2020), this can also come at the cost of increased risk-taking by banks (Kurtzman et al. 2018, Kandrac & Schlusche 2021).

[2]See Altunbas et al. (2010), Delis & Kouretas (2011), Dell'Ariccia et al. (2014) and Bikker & Vervliet (2018).

effect[3] (Cordella & Yeyati 2003) or through a reduction in undiversifiable contagion risk across banks (Diamond & Rajan 2005, Dell'Ariccia & 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 & Yorulmazer 2007*a*,*b*, Diamond & Rajan 2009*b*, Farhi & Tirole 2012). Berger et al. (2017) employ the U.S. Troubled Assets Relief Programme (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.

We study the heterogenous 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 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 & Darmouni (2017) and Luck & Zimmermann (2020). We exploit the cross-sectional variation across holdings of mortgage-backed securities (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.[4] 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 share 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 inter-relations 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. This is consistent with the previous literature where Gambacorta (2009), Altunbas et al. (2010), Delis & Kouretas (2011) and more recently Kandrac & Schlusche (2021) find a negative relation between monetary policy (conventional and unconventional) and bank risk-taking, thus confirming the existence of the bank

[3]Bank's charter value is an indicator of bank's incentive to take risk or private cost of failure. See Keeley (1990).

[4]There are several reasons why banks that held more mortgage-backed securities benefited more from the large scale asset programmes. 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 & Schlusche 2021).

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 programmes were supportive in the recovery of the banking sector post the GFC. Our results are consistent with Berger et al. (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 that discusses the data and identification strategy. Section 4 presents our results, while Section 5 concludes.

2. Theoretical Framework

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.[5] Borio & Zhu (2012) refer to the *"risk taking channel"* of monetary policy as prolonged periods of low interest rates that can alter 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 & Ratnovski (2013), Jiménez et al. (2014), Ioannidou et al. (2014), and Paligorova & Santos (2017), show that banks loosen lending standards

[5] Studies such as those of Acharya et al. (2009) and Diamond & Rajan (2009*a*) 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.

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 et al. 2014), and change in expected default frequency (Gambacorta 2009) to z-scores (Laeven & Levine 2009, Schaeck & Čihák 2010, Beck et al. 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, Kurtzman et al. (2018) and Kandrac & Schlusche (2021) use micro data (bank and loan-level) and find that various QE programmes 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. First, 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 originations (Borio & Zhu 2012, Jiménez et al. 2014, Kandrac & Schlusche 2021). Second, 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). Third, the various QE policies might have induced financial market participants to reallocate portfolios toward riskier and more profitable projects, thereby leading to excessive risk-taking (Abbate & Thaler 2019). Finally, monetary policy can impact bank risk-taking through leverage decisions. Dell'Ariccia et al. (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.

As the FED buys assets from banks through QE, it increases assets (securities) and decreases deposit liability (reserves) 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 non-financial 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 & Zhu 2012). Reaching for yield means that banks maximize the yield spread without paying adequate regard to risk, either by obtaining a higher return on their asset holdings, or 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.

Interest in the relation between monetary policy and bank profitability has gained momentum since the global financial crisis. Accommodative monetary policy creates bank liquidity and lowers the cost of debt, thereby increasing bank capital, lowering loan loss provisioning, and increasing profitability (Bernanke & Gertler 1995, Bernanke et al. 2007, Freixas et al. 2011). At the same time, periods of monetary expansion can have negative effects on bank profits. When interest rates are too low for too long, at first glance, banks might reduce their funding rates to compensate for low lending rates. This should result in a reduction of banks' net interest margins thus hampering the monetary policy transmission mechanism (Alessandri & Nelson 2015, Brunnermeier & Koby 2016, Borio et al. 2017). Therefore, the net effect of monetary policy measures on bank profitability 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.

2.3 Systemic Risk

The literature on unconventional monetary policy thus far focuses on the effects of QE on interest rates (Krishnamurthy & Vissing-Jorgensen 2011), bank lending (Rodnyansky & Darmouni 2017, Luck & Zimmermann 2020), risk-taking (Kandrac & Schlusche 2021) and bank liquidity (Kapoor & 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 et al. (2012) uncover the concept of 'Distress Insurance Premium' using credit default swaps and equity returns. Similarly, Adrian & Brunnermeier (2011) construct the 'CoVaR' that captures the contribution of an institution to the overall systemic risk of the system. Allen et al. (2012) extend the concept of Value at Risk (VaR) by constructing CATFIN, which associates systemic risk to VaR of the financial system. Acharya et al. (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 and measures 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.[6] 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 Centre 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 for NYSE, NYSE MKT, and 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 id was matched with the CRSP permanent company identifier (PERMCO) using the CRSP-FRB Link provided by the Federal Reserve Bank of New York.[7] In order to fully utilize the two datasets, we employ fuzzy matching for all companies that did not have a PERMCO available.[8] Our merged data comprise information on daily returns for 743 unique bank holding companies, with 11,738 BHC-quarter observations in the sample.[9]

To estimate the impact of QE on risk-taking and systemic risk, several key measures are constructed separately from the estimated regressions. First, we compute Z-scores as a measure of bank risk-taking by following Schaeck & Čihák (2010) and Beck et al. (2013). The Z-score is a classic balance

[6] 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.

[7] 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

[8] 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.

[9] The matched data is used in analysing the impact of QE on systemic risk contribution by financial firms and we end up with 288 BHCs and approximately 5,100 BHC-quarter observations after the construction of systemic risk measures.

sheet measure of bank riskiness and has been conceived from the concept of a bank's probability of default. It is often used to either capture the stability of the banking sector (Lee & Hsieh 2014) or the inverse probability of insolvency of a bank (Williams 2016). The Z-score is formally expressed as:

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

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' throughtout the study.

Second, 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 financial firm's leverage are two significant components in the construction of SES.[10] 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:

$$MES_{i,t} = E[R_t^i | R_t^m < C] \tag{2}$$

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 obtain the following formula:

$$SES_{i,t} = 0.15 MES_{i,t-1} + 0.04 LVG_{i,t-1}. \tag{4}$$

[10] MES depends solely on market-based information and estimates individual bank's reaction to the entire stock market when aggregate returns are low.

$SES_{i,t}$ 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, profitablity, 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.[11] Our identification strategy follows Rodnyansky & 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 & Schlusche 2021).

We measure a bank's exposure to QE by the ratio of MBS-to-total assets.[12] 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 1 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.

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:

$$Y_{i,t} = \alpha_i + \beta_t + \rho_{i,t} + \gamma_1' QE_t + \gamma_2 Treat_i + \theta' Treat_i \times QE_t + \delta' X_{i,t-1} + \epsilon_{i,t}. \tag{5}$$

$Y_{i,t}$ denotes the dependent variable and is the measure of individual bank risk-taking, profitability, or bank's contribution to systemic risk across our three specifications. $Treat_i$ is an indicator variable and takes the value of one if a bank belongs to the treatment group and zero 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 one during the episode and zero 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

[11] The choice of time period 2007:Q4 minimizes endogeneity since this is more than six months before QE1.

[12] We also employ MBS-to-securities as an alternative measure of a bank's exposure to QE. The results are consistent with the main results since the ratio of MBS-to-assets and MBS-to-securities are highly correlated in the sample.

interaction term between a bank's treatment status and time dummies corresponding to each QE episode. The vector θ 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.[13]

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 on the construction of the same is presented in Appendix A. The regression also includes bank fixed effects (α_i) to control for fixed differences among banks, and time fixed effects (β_t) to control for differences over time that affect all banks. 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 & Velic 2017, Pesaran 2021). The summary statistics for our dataset and the key variables employed in the study can be seen in Table 1.

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 income indicating that a lower Z-score (higher bank risk taking) is associated with higher net 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

[13] The individual effects of the treatment variable are absorbed by fixed effects in regressions.

risk (column 2). The results suggest that gross relations can obscure the picture of inter-linkages. 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.

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 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 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 11 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 24.3 percent.[14]

Our results complement the findings of Luck & Zimmermann (2020) that show higher loan supply by the treated banks during QE3, a possible channel for increased riskiness as shown in Kurtzman et al. (2018).[15] Our results are also consistent with the previous literature on the impact of conventional monetary policy on bank risk-taking, including Gambacorta (2009), Altunbas et al. (2010), and Delis & Kouretas (2011) among others, that confirms the presence of a risk-taking channel during episodes of expansionary monetary policy.

Table 4 further indicates statistically significant effects for bank risk-taking during QE1 (columns 2 and 6). However, the direction of the coefficients and their economic significance is opposite to the evidence obtained for QE3.[16] In our QE1 sample, banks in the top quartile of the MBS-to-total

[14] More accurate effects can be obtained from $(e^{\theta} - 1) \times 100$.

[15] Although Kurtzman et al. (2018) 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 both due to lower lending standards as well as greater availability of credit.

[16] Since Z-score is a measure of bank stability, a positive coefficient on the interaction term implies high stability and low risk-taking by treated banks during QE1.

assets distribution reduced their risk-taking by 3.1 percent (column 2), relative to banks below the 25^{th} percentile of the MBS distribution. Our understanding of this result is based on the study of Kapoor & Peia (2021), which yields no evidence of loan growth during QE1. Since studies such as that of Kurtzman et al. (2018) 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. By the time QE3 was implemented, banks were more prepared to increase their appetite for risk through higher lending.

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 that reflects the capability of a bank to generate profits from its asset management functions. As before, the main variables of interest 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 75^{th} 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 25^{th} percentile of the MBS distribution. The results hold for different treatment definitions i.e. based on the 10^{th} and 90^{th} 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 & 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 most 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 et al. (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/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 programmes were largely unanticipated, especially the third round, banks that held more MBS had a prompt recovery and reduced their contribution to systemic risk.

4.3 Systems Approach

We also estimate our three specifications in 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.[17] Possible endogeneity issues are further addressed via lags of variables as instruments in the GMM case. As evident from Tables 7 and 8, the system estimates are consistent with the individual regression estimates in Tables 4-6.

4.4 Heterogenous Analysis

4.4.1 *The Impact of QE on Systemic Risk for Too Big To Fail Banks*

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 & 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.

[17] We analyze frameworks with control factors that differ across equations.

We follow Zhou (2009) and identify the TBTF banks in our data.[18] To investigate the impact of QE on systemic risk contributions by TBTF banks, we estimate the following regression model:

$$Y_{i,t} = \alpha_i + \beta_t + \rho_{i,t} + \gamma_1' QE_t + \gamma_2 TBTF_i + \theta' TBTF_i \times QE_t + \delta' X_{i,t-1} + \epsilon_{i,t}, \tag{6}$$

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 & 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), 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 median values of the 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 2007Q4 and 0 if it lies in the bottom half of the distribution. Figure 2 shows a plot of estimated coefficients θ 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:

$$Y_{i,t} = \alpha_i + \beta_t + \rho_{i,t} + \gamma_1' QE_t + \gamma_2 \left(\frac{MBS}{Securities}\right)_i + \theta' \left(\frac{MBS}{Securities}\right)_i \times QE_t + \delta' X_{i,t-1} + \epsilon_{i,t}. \tag{7}$$

This measure has been employed in earlier studies including that of Kurtzman et al. (2018) 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.

[18]We are able to label sixteen 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 in NYSE, and (iii) the banks should be active from the beginning of 1987 until 2009.

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 the amount of equity, leverage ratio, and long-run MES. Following Brownlees & Engle (2016), $SRISK$ is defined as:

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

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 with Brownlees & Engle (2016).[19] 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 et al. (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 a greater cushion to absorb losses and reduce probabilities of financial distress or failure.

Our results suggest that banks were encouraged to increase their risk-taking capacity and prof-

[19]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.

itability 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 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.

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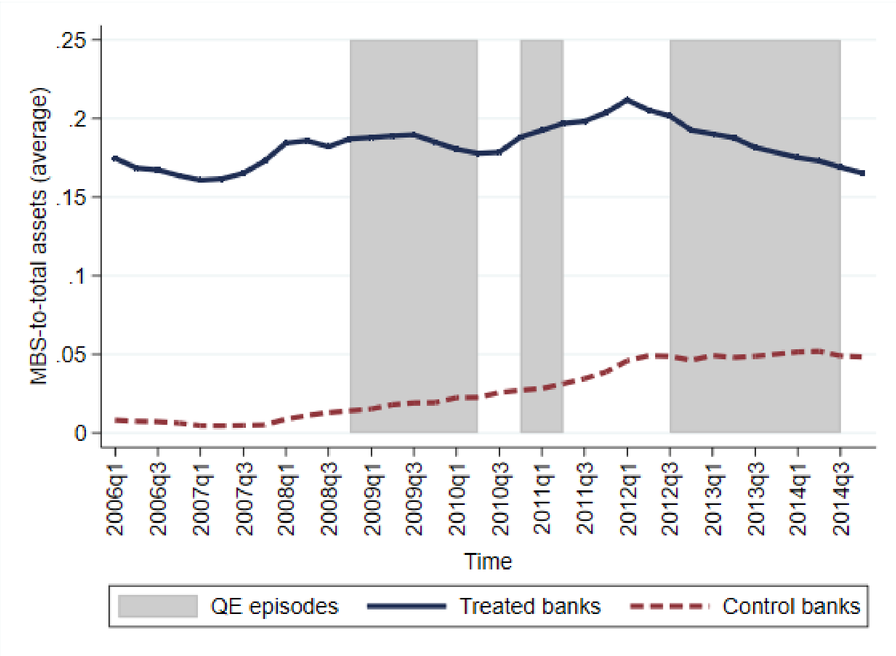
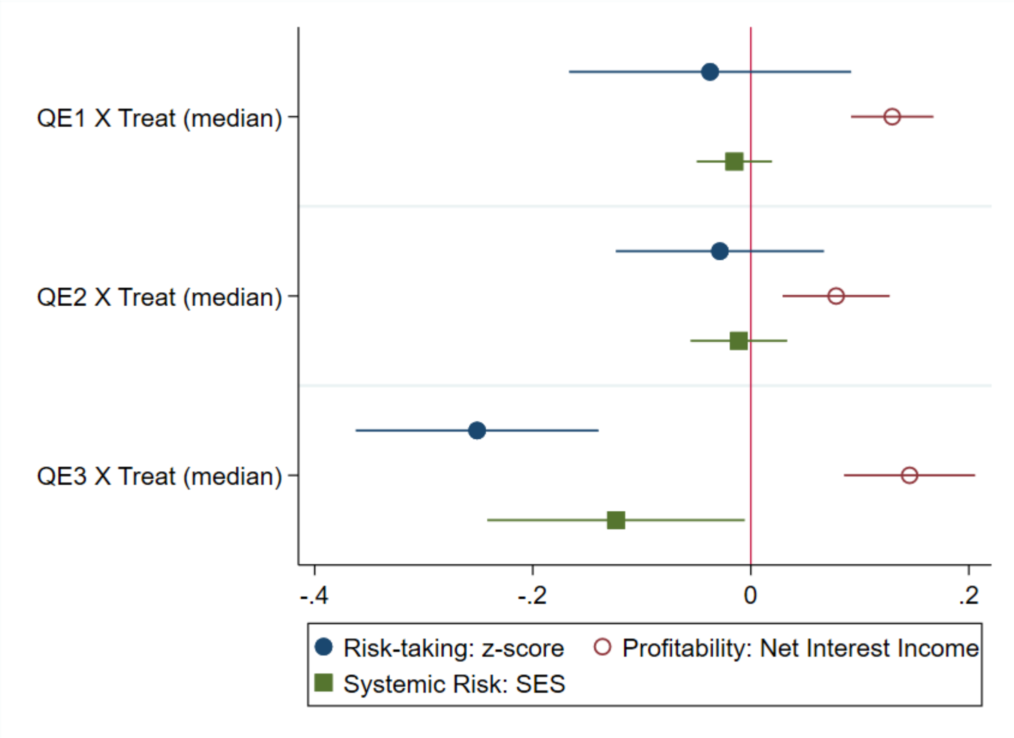
Figures

Figure 1: MBS-to-total assets for treated and control banks



Notes: 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 MBS-to-total assets ratio in 2007Q4, while control are in the bottom quartile (bottom 25 percent) of the distribution. Shaded areas highlight the three episodes of QE

Figure 2: Robustness test: treatment variable based on median



Notes: The figure shows coefficient estimates where dependent variable are the logarithm of Z-score, logarithm of net interest income and the change in systemic expected shortfall. The regression uses an alternative treatment definition as a dummy equal 1 if banks have an above the median ratio of MBS to total assets in 2007Q4 and 0 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.

Tables

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:						
$\ln(Z - score)$	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
$\Delta \ln(SES)$	-3.1	1.00	-3.3	-3.25	-3.19	5,087
$SRISK$	-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

Notes: Summary statistics recorded from 2006Q1 to 2014Q4 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 $SRISK$ are alternative measures of bank risk-taking, profitability, and systemic risk respectively in robustness checks.

Table 2: Pearson gross correlations

Variable	**Z-score**	**Net Income**	**SES**
Z-score	1.0000		
Net Income	-0.0599***	1.0000	
SES	-0.1593***	0.0119	1.0000

Notes: The variables Z-score and net interest income are expressed in natural logarithms, while SES is defined as the change in systemic expected shortfall. ***, **, * represent significance at the 1%, 5% and 10%, respectively.

Table 3: Baseline partial correlations

	Z-score	**SES**	
	(1)	(2)	(3)
Net Interest Income	-0.091*	-0.052*	
	(0.050)	(0.027)	
Z-score			0.023**
			(0.009)
Size	0.082	0.055**	0.003
	(0.050)	(0.028)	(0.006)
Liquidity	-1.554***	0.316***	0.466***
	(0.091)	(0.058)	(0.081)
Tier 1 Capital Ratio	0.023***	0.005**	0.001
	(0.005)	(0.003)	(0.004)
Leverage ratio	0.065***	-0.018***	-0.022***
	(0.007)	(0.004)	(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

Notes: The dependent variable in column (1) is logarithm of Z-score, while in columns (2) and (3) 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. ***, **, * represent significance at the 1%, 5% and 10%, respectively.

Table 4: The impact of QE on bank risk-taking

	Z-score					
	(1)	(2)	(3)	(4)	(5)	(6)
$QE1_t \times Treat_i^Q$	0.019	0.031**				
	(0.017)	(0.015)				
$QE2_t \times Treat_i^Q$	0.016	-0.006				
	(0.021)	(0.018)				
$QE3_t \times Treat_i^Q$	-0.046**	-0.048**				
	(0.019)	(0.021)				
$QE1_t \times Treat_i^D$			-0.005	0.009		
			(0.029)	(0.025)		
$QE2_t \times Treat_i^D$			0.028	-0.018		
			(0.040)	(0.027)		
$QE3_t \times Treat_i^D$			-0.042	-0.110***		
			(0.027)	(0.031)		
$QE1_t \times (\frac{MBS}{TotalAssets})_i$					0.111	0.170**
					(0.082)	(0.076)
$QE2_t \times (\frac{MBS}{TotalAssets})_i$					0.208**	0.105
					(0.095)	(0.088)
$QE3_t \times (\frac{MBS}{TotalAssets})_i$					-0.083	-0.243**
					(0.086)	(0.096)
Observations	11,354	10,127	4,568	4,082	22,165	19,720
R-squared	0.673	0.690	0.675	0.692	0.666	0.684
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

Notes: The dependent variable in columns (1)-(6) is logarithm of Z-scores. $Treat_i^Q$ takes the value one for banks in the top quartile (top 25 percent) of the MBS-to-total assets distribution, while zero for banks in the bottom quartile (bottom 25 percent) of the distribution. $Treat_i^D$ takes the value one for banks in the top decile (top 10 percent) of the MBS-to-total assets ratio, and zero for banks in the bottom decile (bottom 10 percent) of the distribution. $(\frac{MBS}{TotalAssets})_i$ is the ratio of MBS to total assets in 2007Q4. $QE1_t$, $QE2_t$ 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. 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. ***, **, * represent significance at the 1%, 5% and 10%, respectively.

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***	0.061***				
	(0.008)	(0.006)				
$QE2_t \times Treat_i^Q$	0.045***	0.050***				
	(0.011)	(0.008)				
$QE3_t \times Treat_i^Q$	0.076***	0.038***				
	(0.012)	(0.010)				
$QE1_t \times Treat_i^D$			0.082***	0.074***		
			(0.012)	(0.009)		
$QE2_t \times Treat_i^D$			0.058***	0.048***		
			(0.016)	(0.012)		
$QE3_t \times Treat_i^D$			0.078***	0.019*		
			(0.017)	(0.010)		
$QE1_t \times (\frac{MBS}{TotalAssets})_i$					0.340***	0.354***
					(0.040)	(0.033)
$QE2_t \times (\frac{MBS}{TotalAssets})_i$					0.238***	0.271***
					(0.057)	(0.048)
$QE3_t \times (\frac{MBS}{TotalAssets})_i$					0.467***	0.253***
					(0.062)	(0.056)
Observations	12,785	11,040	5,148	4,445	24,995	21,523
R-squared	0.978	0.991	0.977	0.992	0.980	0.992
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

Notes: The dependent variable in columns (1)-(6) is logarithm of net interest income. $Treat_i^Q$ takes the value one for banks in the top quartile (top 25 percent) of the MBS-to-total assets distribution, while zero for banks in the bottom quartile (bottom 25 percent) of the distribution. $Treat_i^D$ takes the value one for banks in the top decile (top 10 percent) of the MBS-to-total assets ratio, and zero for banks in the bottom decile (bottom 10 percent) of the distribution. $(\frac{MBS}{TotalAssets})_i$ is the ratio of MBS to total assets in 2007Q4. $QE1_t$, $QE2_t$ 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. 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. Control variables include bank size, liquidity, tier 1 capital ratio and leverage ratio. All control variables are taken as lagged. Constant terms included but not reported. Robust standard errors in parentheses. ***, **, * represent significance at the 1%, 5% and 10%, respectively.

Table 6: The impact of QE on systemic risk

	Systemic Expected Shortfall					
	(1)	(2)	(3)	(4)	(5)	(6)
$QE1_t \times Treat_i^Q$	-0.013	-0.015				
	(0.018)	(0.018)				
$QE2_t \times Treat_i^Q$	-0.012	-0.011				
	(0.022)	(0.023)				
$QE3_t \times Treat_i^Q$	-0.109*	-0.124**				
	(0.057)	(0.060)				
$QE1_t \times Treat_i^D$			-0.025	-0.023		
			(0.039)	(0.039)		
$QE2_t \times Treat_i^D$			-0.025	-0.016		
			(0.051)	(0.053)		
$QE3_t \times Treat_i^D$			-0.116	-0.047		
			(0.099)	(0.097)		
$QE1_t \times (\frac{MBS}{TotalAssets})_i$					-0.093	-0.099
					(0.141)	(0.074)
$QE2_t \times (\frac{MBS}{TotalAssets})_i$					-0.052	-0.033
					(0.219)	(0.092)
$QE3_t \times (\frac{MBS}{TotalAssets})_i$					-0.340*	-0.472*
					(0.192)	(0.274)
Observations	1,855	1,819	738	733	3,687	3,613
R-squared	0.202	0.196	0.133	0.139	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

Notes: The dependent variable in columns (1)-(6) is the change in SES. $Treat_i^Q$ takes the value one for banks in the top quartile (top 25 percent) of the MBS-to-total assets distribution, while zero for banks in the bottom quartile (bottom 25 percent) of the distribution. $Treat_i^D$ takes the value one for banks in the top decile (top 10 percent) of the MBS-to-total assets ratio, and zero for banks in the bottom decile (bottom 10 percent) of the distribution. $(\frac{MBS}{TotalAssets})_i$ is the ratio of MBS to total assets in 2007Q4. $QE1_t$, $QE2_t$ 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. 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. ***, **, * represent significance at the 1%, 5% and 10%, respectively.

Table 7: The impact of QE on bank risk-taking, profitability and systemic risk: Seemingly Unrelated Regressions

	Z-Score (1)	**NII** (2)	**SES** (3)
$QE1_t \times Treat_i^Q$	-0.098	0.091	-0.010
	(0.126)	(0.071)	(0.032)
$QE2_t \times Treat_i^Q$	0.028	0.081	-0.011
	(0.204)	(0.114)	(0.051)
$QE3_t \times Treat_i^Q$	-0.304*	0.202**	-0.113**
	(0.176)	(0.099)	(0.044)
Observations	1,686	1,686	1,686
R-squared	0.715	0.801	0.044
QE_t	Yes	Yes	Yes
Treatment variable	Yes	Yes	Yes

Notes: Pooled regressions employed. The dependent variable in column (1) is the logarithm of Z-score, in columns (2) is the logarithm of net interest income and in column (3) is the change in systemic expected shortfall (SES). $Treat_i^Q$ takes the value one for banks in the top quartile (top 25 percent) of the MBS-to-total assets distribution, while zero 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. 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. ***, **, * represent significance at the 1%, 5% and 10%, respectively.

Table 8: The impact of QE on bank risk-taking, profitability and systemic risk: System GMM

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

Notes: 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 and in column (3) is the change in systemic expected shortfall (SES). $Treat_i^Q$ takes the value one for banks in the top quartile (top 25 percent) of the MBS-to-total assets distribution, while zero 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. The regression employs bank size, liquidity, leverage ratio, deposit ratio and tier 1 capital raio in lagged terms. 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. ***, **, * represent significance at the 1%, 5% and 10%, respectively.

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	-0.006
	(0.015)	(0.014)
$QE2_t \times TBTF_i$	-0.080*	-0.081*
	(0.043)	(0.045)
$QE3_t \times TBTF_i$	-0.138**	-0.147**
	(0.061)	(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	No
Year-Quarter Fixed Effects	Yes	Yes
Bank Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes

Notes: The dependent variable is the growth rate of SES. $TBTF_i$ is a dummy that takes the value one for banks that are identified as the Systemicaaly Important Financial Institutions (SIFIs) by the Financial Stability Board and 0 otherwie. $QE1_t$, $QE2_t$ 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. All control variables are taken as lagged. 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. ***, **, * represent significance at the 1%, 5% and 10%, respectively.

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)
$QE1_t \times Treat/Sec_i^Q$	0.005	0.014	0.038***	0.043***	-0.015	-0.016
	(0.018)	(0.017)	(0.008)	(0.006)	(0.022)	(0.021)
$QE2_t \times Treat/Sec_i^Q$	-0.038*	-0.031	0.041***	0.050***	0.001	-0.000
	(0.022)	(0.019)	(0.011)	(0.008)	(0.035)	(0.034)
$QE3_t \times Treat/Sec_i^Q$	-0.095***	-0.071***	0.068***	0.043***	-0.065**	-0.077**
	(0.020)	(0.021)	(0.011)	(0.008)	(0.030)	(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

Notes: 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 change in systemic expected shortfall (SES). $Treat/Sec_i^Q$ takes the value one for banks in the top quartile (top 25 percent) of the MBS-to-securities distribution, while zero 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. The regression employs bank size, liquidity, leverage ratio, deposit ratio and tier 1 capital raio in lagged terms. 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 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. ***, **, * represent significance at the 1%, 5% and 10%, respectively.

Table 11: Varying measures of dependent variable

	Risk/TA (1)	**ROA** (2)	**SRISK** (3)
$QE1_t \times Treat_i^Q$	-0.005***	0.001***	0.174
	(0.002)	(0.000)	(0.346)
$QE2_t \times Treat_i^Q$	0.010***	0.001***	-0.782
	(0.002)	(0.000)	(0.550)
$QE3_t \times Treat_i^Q$	0.013***	0.001***	-0.684*
	(0.002)	(0.000)	(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

Notes: 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 one for banks in the top quartile (top 25 percent) of the MBS-to-total assets distribution, while zero 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. 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. All control variables are taken as lagged. Constant terms included but not reported. Robust standard errors in parentheses. ***, **, * represent significance at the 1%, 5% and 10%, respectively.

A. Variables employed: construction and corresponding definitions

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 divided by total asset (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 undercapitazed	CRSP & FR-Y9C
SRISK	Amount of capital that is required by a financial institution during periods of crisis	CRSP & FR-Y9C

Notes: Table presents data sources and method of construction of variables used in analysis. FR-Y9C refers to balance sheet information of all BHCs from Federal Reserve Bank of Chicago. CRSP refers to market data in Centre for Research in Security Prices database.