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Alzuabi, Raslan and Caglayan, Mustafa and Mouratidis, Kostas

University of Sheffield, Heriot-Watt University, University of Sheffield

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The Risk-Taking Channel in the US: A GVAR Approach

Raslan Alzuabi*
Department of Economics, University of Sheffield
Mustafa Caglayan†
School of Social Sciences, Heriot-Watt University
Kostas Mouratidis‡
Department of Economics, University of Sheffield

Abstract

Using a panel of large US banks, we examine banks' risk-taking behaviour in response to monetary policy shocks. Our investigation provides support for the presence of a risk-taking channel: banks' nonperforming loans increase in the medium to long-run following an expansionary monetary policy shock. We also find that banks' capital structure plays an important role in explaining bank's risk-taking appetite. Impulse response analysis shows that shocks emanating from larger banks spillover to the rest of the sector but no such effect is observed for smaller banks. These findings are confirmed for banks' Z-score.

Keywords: Risk-taking channel: GVAR: Monetary policy shocks; Spillover effects; Impulse response analysis.
JEL: E44; E52; G01; G19; G29.

*Department of Economics, University of Sheffield, 9 Mappin Street S1 4DT, UK. E-mail: raslan.alzuabi@sheffield.ac.uk

†Corresponding author; School of Social Sciences, Heriot–Watt University, Edinburgh EH14 4AS, UK. Tel: +44 (0) 131 451 8373; E-mail: m.caglayan@hw.ac.uk.

‡Department of Economics, University of Sheffield, 9 Mappin Street S1 4DT, UK. E-mail: k.mouratidis@sheffield.ac.uk

1 Introduction

Long before the global financial crisis, Rajan (2006) has predicted a perfect storm that will hit the US and the rest of the world economies. He argued that a setting with low returns followed by a period of high rates could lead to a sharp and messy realignment because of managers' search for yield as asset prices revalue.[1] The realignment of financial markets that followed the collapse of the Lehman Brothers in 2008 proved him right.

Following the financial crisis in 2008, researchers begun to examine the link between monetary policy and financial institutions' appetite for risk.[2] Based on the underpinnings of the theoretical research on the risk-taking channel (e.g. see Borio and Zhu, 2012), several researchers provided evidence that in an environment with low interest rates, banks exhibit risk-taking behaviour. For example, Jiménez et al. (2014), using a unique bank level dataset for Spain, showed that bank loans to borrowers with bad credit history and higher probability of default increase following a reduction in the overnight rates. Examining bank level data from Bolivia, the US and the EU, similar observations were reported by Ioannidou et al. (2015), Altunbas et al. (2014) and Angeloni et al., 2015. In contrast, De Graeve et al. (2008), using a model that examines the interaction between bank-level distress and macroeconomic risk, found that the probability of distress declines after a positive monetary policy shock. Buch et al. (2014a) have provided strong evidence that the response of a forward-looking bank risk to an expansionary monetary policy shock varies across different types of banks. In particular, they found that small domestic banks increase their exposure to risk while large domestic banks do not change their risk exposure and foreign owned banks take on more risk.

In this context, Dell'Ariccia et al. (2017) argue that when banks are allowed to adjust their capital structures, lower interest rates lead to greater leverage and higher risk. However, if the capital structure is fixed, the impact of a reduction in interest rates on bank risk depends on the degree of bank capitalization: well-capitalized banks increase risk, while highly levered

[1] In an earlier paper Borio and Lowe (2002) have shown that financial imbalances may develop in high growth, low inflation, low interest rate economies which eventually require a monetary response to preserve both financial and monetary stability.

[2] We do not suggest that monetary policy causes banks to adopt risk-taking behaviour. Monetary policy authorities aim to keep the policy rate as close as possible to the equilibrium interest rate. If the equilibrium rate happens to be low then the policy rate naturally should be low. To that end, the safe asset literature provides a compelling explanation why US rates could have been low (see for instance, Negro et al., 2017 and Krishnamurthy and Vissing-Jorgensen, 2012).

banks may decrease it, if loan demand is linear or concave. Also it is useful to recall the financial accelerator model developed by Bernanke et al. (1996) which implies that lower interest rates may have countervailing effects on bank risk. In particular, while low interest rates would reduce bank risk by decreasing the interest burden of firms, it would also increase the collateral value and borrowing capability of high-risk firms.[3]

In this study, we contribute to the empirical literature of risk-taking channel by implementing a flexible econometric framework, which accounts both for the heterogeneity of banks' risk-taking behaviour in response to monetary policy shocks and for the transmission of shocks across banks (spillover effects) with differing characteristics. We use the Global Vector Autoregression (GVAR) methodology (see Pesaran et al., 2004) to estimate the potential interactions among a large set of variables by decomposing the underlying large VARs into smaller conditional models that are linked together through their cross-sectional averages while no restrictions are imposed on the dynamics of the individual sub-models.[4] In this setting, we can address issues that have not been examined earlier such as the spillover effects or the heterogeneity of banks' responses to monetary policy shocks.[5]

An additional contribution we make to this literature relates to the identification of monetary policy shocks, as this problem constitutes a major challenge when examining the linkages between the monetary transmission mechanism and the risk-taking channel. It is well known that the use of a monetary shock which is not properly identified would yield biased results in relation to its true causal effects on banks' risk-taking behaviour. The main difficulty in gauging the link between low interest rates and banks' risk-taking behaviour is to isolate changes in monetary policy from the impact of expected default. Although, one can argue that monetary policy is exogenous to the future default rate, because financial stability is not included directly in the bank's loss function, the fact that defaults are related to future economic conditions suggests for the presence of an indirect association between

[3]Furthermore, recent DSGE models have different implications about the role of monetary policy on bank risk. Angeloni and Faia (2013) show that monetary expansion and a positive productivity shock increase bank leverage and risk while Zhang (2009) argues that the reverse is true.

[4]A fundamental problem of global models is the curse of dimensionality, which arises when the number of variables is large compared to the time dimension. Developing a global VAR approach, Pesaran et al. (2004) were able to overcome this problem and analyze global interdependencies and the propagation of shocks across countries.

[5]Alternatives to GVAR modeling approach are the factor augmented VAR (FAVAR) model or the panel VAR (PVAR). Both FAVAR and PVAR can be viewed as data shrinkage processes. While in the former model it is difficult to identify the unobserved factors, the latter approach in certain cases becomes operational by imposing restrictions on the autoregressive coefficients.

the current monetary policy and the expected default rates.[6,7] Therefore, in investigating the effects of monetary policy on banks' risk-taking attitude, one should account for the presence of endogeneity between the proxy for monetary policy and credit risk, as these variables would respond simultaneously to expected macroeconomic conditions.[8]

To overcome the problem of endogeneity, we follow the Romer and Romer (2004) (hereafter RR) approach by regressing the intended fund rate changes on the contemporaneous rate of unemployment and on the Fed's internal forecast of inflation and of real economic activity. In our investigation, we modify the RR approach such that the parameters of the model are allowed to be time-variant with regime switching.[9] We follow this route because the RR approach imposes the restriction that the role of forward-looking variables in the central bank's reaction function remains constant across time. Our modification is consistent with the findings of Barakchian and Crowe (2013) who argued that not only the Fed has become more forward-looking after 1988 but also a monetary policy shock based on RR approach was subject to structural breaks and time-variation.

We examine the presence of a risk-taking channel by scrutinizing the response of banks' nonperforming loans to total loans ratio as monetary policy changes. We find that in the short-run, banks' nonperforming loans moderately decline in response to an expansionary monetary policy shock. However, in the medium-run, nonperforming loans tend to increase for most of the banks in our sample, suggesting the prevalence of a risk-taking channel. Furthermore, our investigation shows that although in the short-run the reaction of banks to an expansionary policy shock is rather homogeneous, in the medium- and the long-run, the magnitude and the duration of banks' reactions vary. We provide evidence that banks' heterogeneous risk-taking responses relate to their capital structure. Finally, when we examine the impulse response functions, we provide evidence that bank size plays an important role in the transmission of shocks (spillover effects): an adverse shock to the nonperforming loans of a large bank would lead to an immediate and long lasting impact on the remaining banks within the system, while no such effect is observed when the adverse shock emanates from

[6]Bernanke and Gertler (1999) argue that the central bank should react to asset prices only if the latter undermines inflation stability.

[7]The minutes of the Federaral Open Market Committee (FOMC) did not discuss issues of financial stability before the crisis of 2007. See for instance Bernanke (2008).

[8]For example, Ioannidou et al. (2015) argue that during periods of financial uncertainty central banks tend to reduce the interest rate.

[9]Also see Caglayan et al. (2017) who followed a similar reasoning to examine the role of financial depth on the asymmetric impact of monetary policy shocks on output growth.

a smaller bank. We confirm our findings using banks' Z-score as an alternative measure for bank risk. We examine the presence of a risk-taking channel of monetary policy under normal economic conditions: the investigation uses quarterly data over the period from 1985Q1 to 2007Q4.

The rest of this study is structured as follows. Section 2 provides a brief review of the literature on the risk-taking channel. Section 3 explains our methodology. Section 4 provides information on the data as well as the construction of the monetary policy shock and bank risk measures. Section 5 presents our empirical observations. Section 6 concludes the paper.

2 A brief literature review

Borio and Zhu (2012) suggest that there are at least three ways through which the risk-taking channel may operate when interest rates are kept low or declining for a long period. First, they argue that a reduction in the interest rate leads to an increase in collateral and asset values of borrowers, which in turn influences banks' risk perceptions or risk tolerance and increase banks' lending. In this context lending is driven by banks' willingness to take on more risk rather than improvements in debtors' collateral and repayment capacity.[10] The second channel (referred to as 'search for yield' by Rajan, 2006) relates to the linkages between a bank manager's target return and the market rate of return. This channel operates through financial institutions' desire to engage in risky investment activities, as they are obliged to reduce the gap between the yield on highly rated government bonds and the minimum guaranteed rate of return linked to their liabilities.[11] Thirdly, transparency may enhance the perception that the central bank's actions would cut off large downside risks encouraging risk taking.

All three channels indicate that monetary policy easing will induce greater risk taking. However, these channels will not operate in a similar way across different banks, different banking systems and time. An analytical model provided by Dell'Ariccia et al. (2017) predicts that the strength of the relationship between the policy rate and bank risk taking is a function of bank's capital structure, borrowers' collateral and monitoring cost. In particular, they show that the policy rate has a negative association with banks' risk-taking behaviour which relates to the capitalization of banks.

[10]This mechanism is similar but broader in spirit to the financial accelerator mechanism. See, for instance, Bernanke et al. (1996), Bernanke and Gertler (1995) and Chen (2001).

[11]In some countries, such as Switzerland, a minimum rate of return is reinforced by regulation.

Using bank level data, empirical researchers have examined the risk-taking channel by scrutinizing whether banks extend loans to riskier borrowers during low interest rate periods. To that end, Jiménez et al. (2014), using loan-level data from the Spanish Credit Register, have shown that lower overnight interest rates induces less capitalized banks to grant more loans to ex-ante risky firms. They showed that these banks also commit to larger loan volumes with fewer collateral requirements to firms which have a higher ex-post likelihood of default. Ioannidou et al. (2015) have examined the impact of the federal funds rate on the riskiness and pricing of new bank loans granted in Bolivia. They reported evidence that initiating loans with a subprime credit rating or loans to riskier borrowers with current or past non-performance become more likely when the federal funds rate is low.[12] Maddaloni and Peydro (2011), using data from the US and Europe, have shown that banks' risk tolerance increases when the short-term interest rate is low but not when the long-term interest rate changes. Similar results are reported by Altunbas et al. (2014) and Angeloni et al. (2015) who examined a sample of banks in Europe and the US.

Other researchers have shown that the impact of monetary expansion on bank risk might be different across the banking system, time and banking groups. For instance, Buch et al. (2014b), using a FAVAR model, which included both macro and bank level data from the Call Reports, have shown that a backward-looking bank risk decline after a monetary policy loosening, which is contradictory to the results found in the papers discussed above. Buch et al. (2014a), using data from the Survey of Terms of Business Lending in the US, have shown that there is no evidence of increased risk taking for the entire banking system after an expansionary monetary policy shocks or an unexpected increase of housing prices. However, they argued that there are important differences across banking groups. In particular, they showed that bank risk increases for small domestic banks while it declines for foreign banks and remains unchanged for large domestic banks. Furthermore, De Graeve et al. (2008) have provided evidence of a decline in German banks' probability of distress after a monetary policy loosening.

We adopt an approach that differs from the literature by employing a GVAR model to investigate banks' risk-taking behaviour. We also discuss whether there is any type of systematic heterogeneity in the way banks react to exogenous shocks and examine the possibility

[12] Note that in both Jiménez et al. (2014) and Ioannidou et al. (2015) monetary policy is exogenously given. In the former case monetary policy is determined by the ECB while in the latter by the Fed.

of spillover effects across banks. Finally, we confirm our findings using banks' Z-score as an alternative measure of risk. In what follows, we discuss our empirical methodology and our findings.

3 Econometric methodology

An investigation regarding the impact of monetary policy and macroeconomic shocks on bank risk while accounting for possible spillover and feedback effects requires a coherent global model that includes a large set of variables from many institutions. There are a few methodologies that one may implement for such an investigation. A standard framework to examine the transmission of shocks across banks and time is VAR models. However, unrestricted VAR models cannot be estimated due to the large number of unknown parameters.

To get around the curse of dimensionality, researchers have proposed alternative approaches. For example, factor models can be interpreted as data shrinkage procedures, which summarize the information of a large set of variables in few factors augmented by a small set of observed variables (i.e. FAVAR models). Yet, the economic interpretation of the extracted factors is a difficult task. Alternatively, panel VARs or large scale Bayesian VARs solve the problem of dimensionality by shrinking the parameter space.[13] In particular, Canova and Ciccarelli (2013) show that a panel VAR shrinks the parameter space by assuming that the unknown parameters can be decomposed into components that are common across cross-sectional units and variables, common within cross-section units, a variable specific component and lag specific component.

Unlike the panel VAR, the GVAR approach solves the dimensionality problem by breaking down the underlying large VAR model into a small number of conditional models which are linked together via their cross-sectional averages. That is, the GVAR methodology imposes an intuitive restriction on cross-sectional linkages without imposing any restriction on the dynamics of individual units, allowing the researcher to investigate the transmission of real and financial shocks across countries, regions and financial intermediaries. In this context, the GVAR approach lets us capture the risk of contagion within the financial system, which has became more pronounced due to increasing financial integration and complex linkages throughout the financial intermediaries.

[13]The difference between a Bayesian large scale VAR and a panel VAR is that the former treat all variables symmetrically while the latter takes into account the structure of the variables (for details see Pesaran, 2015).

3.1 The GVAR model

We consider a world of N banks indexed by i=$1, 2, ...N$, and denote a $k_i \times 1$ vector of bank specific variables, $\mathbf{x}_{it}$, and of bank specific foreign variables $\mathbf{x}^*_{it}$ =$\Sigma_{j=1}^{N} w_{ij} x_{jt}$ where $w_{ij} \geq 0$ is a sequence of bank specific weights with $\Sigma_{j=i}^{N} w_{ij} = 1$ and $w_{ii} = 0$. We construct the associated weights based on banks' bilateral interbank exposure, which we constructed using banks' aggregate interbank assets and liabilities. In doing so we assume that each bank borrows and lends as widely as possible across all banks. This assumption implies that the exposure of bank i to bank j is increasing both with the total interbank lending of bank i and total interbank borrowing of bank j. In that sense, bank exposure reflects the relative importance of an institution in the interbank market. In constructing the weights, we also assume that the largest bank acts as a money center for the other banks in the system.[14]

The bank specific $VARX^*(p_i, q_i)$ can be written as:[15]

$$\Phi_i(L, p_i)\mathbf{x}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \mathbf{\Psi}_i(L, q_i)\mathbf{d}_t + \mathbf{\Lambda}_i(L, q_i)\mathbf{x}^*_{it} + \mathbf{u}_{it}, \tag{1}$$

where L is the lag operator, $\Phi_i(L, p_i) = \mathbf{I}_{k_i} - \sum_{l=1}^{p_i} \Phi_l L^l$, $\mathbf{\Lambda}_i(L, q_i) = \sum_{l=0}^{q_i} \Lambda_l L^l$ and $\mathbf{\Psi}_i(L, q_i) = \sum_{l=0}^{q_i} \Psi_l L^l$ are matrix polynomials, $\mathbf{d}_t$ is a $g \times 1$ vector of observed common variables such as regulatory and shifts dummies. The vector of bank-specific idiosyncratic shocks is denoted by $\mathbf{u}_{it}$, where $E(u_{it}u'_{js}) = \mathbf{\Sigma}_{ij}$ for $t = s$ and $E(u_{it}u'_{js}) = 0$ for $t \neq s$. The dimensions of $\mathbf{a}_{i\eta}$ $(\eta = 0, 1)$ are $k_i \times 1$ while the dimension of $\Phi_l, \mathbf{\Lambda}_i,$ $\mathbf{\Psi}_i$ are $k_i \times k_i$, $k_i \times k^*_i$ and $k_i \times g$, respectively. Equation (1) indicates that spillover effects across banks can occur through three distinct but interrelated channels: a) direct and lagged impact of x^*_{it} on x_{it}; b) dependence of bank specific variables on common global exogenous variables (i.e. $\mathbf{d}_t$); and c) non-zero contemporaneous dependence of shocks via cross-bank covariances Σ_{ij}.

Reordering equation 1, we obtain:

$$\mathbf{A}_i(L, p_i, q_i)\mathbf{z}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \mathbf{\Psi}_i(L, q_i)\mathbf{d}_t + \mathbf{u}_{it}, \tag{2}$$

[14] Problems of this type can be solved by using a matrix-balancing algorithm known as RAS algorithm. The approach discussed here has been used by Upper and Worms (2004) and Wells (2004). See Appendix A for details.

[15] $VARX^*(p_i, q_i)$ models with weakly exogenous non-stationary variables have been introduced by Harbo et al. (1998) and Pesaran et al. (2000).

where

$$\mathbf{z}_{it} = [\mathbf{x}_{it}, \mathbf{x}_{it}^{*}]'$$

$$\mathbf{A}_i(L, p_i, q_i) = [\Phi_i(L, p_i) - \mathbf{\Lambda}_i(L, q_i)].$$

Let $p = \max(p_i, q_i)$ and construct $\mathbf{A}_i(L, p) = \sum_{l=0}^{p} \mathbf{A}_{il} L^l$ then (2) can be written as

$$\mathbf{A}_{i0}\mathbf{z}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \sum_{l=1}^{p} \mathbf{A}_{il}\mathbf{z}_{it-l} + \sum_{l=0}^{p} \Psi_{il}\mathbf{d}_{t-l} + \mathbf{u}_{it}, \tag{3}$$

where $\mathbf{A}_{i0} = (\mathbf{I}_{k_i}, -\mathbf{\Lambda}_{i0})$, $\mathbf{A}_{il} = (\Phi_{il}, \mathbf{\Lambda}_{il})$ for $l = 1, 2, ...p$, $\Phi_{il} = 0$ for $l > p_i$ and $\mathbf{\Lambda}_{il} = 0$ for $l > q_i$. Estimation of (3) is the first step of the GVAR approach. The second step consists of stacking N bank specific models in one large global VAR. Letting $\mathbf{x}_t = [\mathbf{x}'_{1t}, \mathbf{x}'_{2t}, ...\mathbf{x}'_{Nt}]'$ and using the $(k_i + k_i^*) \times k$ link matrices $\mathbf{W}_i = [\mathbf{E}'_i, \widetilde{\mathbf{W}_i}']$, where $\mathbf{E}$ is a $k \times k_i$ dimensional selection matrix so that $\mathbf{x}_{it} = \mathbf{E}'_i\ \mathbf{x}_t$ and $\widetilde{\mathbf{W}}_i$ is $k \times k_i^*$ so that $\mathbf{x}_{it}^* = \widetilde{\mathbf{W}}'_i\mathbf{x}_t$, we have[16]:

$$\mathbf{z}_{it} = \begin{pmatrix} \mathbf{x}_{it} \\ \mathbf{x}_{it}^* \end{pmatrix} = \mathbf{W}_i\mathbf{x}_t. \tag{4}$$

Substituting (4) into (3) yields

$$\mathbf{A}_{i0}\mathbf{W}_i\mathbf{x}_t = \mathbf{a_{i0}} + \mathbf{a}_{i1}t + \sum_{l=1}^{p} \mathbf{A}_{il}\mathbf{W}_i\mathbf{x}_{t-l} + \sum_{l=0}^{p} \Psi_{il}\mathbf{d}_{t-l} + \mathbf{u}_{it}, \tag{5}$$

and stacking these models for $i = 1, 2, ...N$, we obtain

$$\mathbf{G}_0\mathbf{x}_t = \mathbf{a_0}+\mathbf{a}_1\mathbf{t} + \sum_{l=1}^{p} \mathbf{G}_l\mathbf{x}_{t-l}+\sum_{l=0}^{p} \mathbf{\Psi}_l\mathbf{d}_{t-l} + \mathbf{u}_t, \tag{6}$$

[16] where $\mathbf{x}_{it}^* = \widetilde{\mathbf{W}}'_i\mathbf{x}_t = [w_{i1}\mathbf{I}_{k1}\ w_{i2}\mathbf{I}_{k2} \cdots w_{iN}\mathbf{I}_{kN}]\,[\mathbf{x}_{1t}\ \mathbf{x}_{2t} \cdots \mathbf{x}_{Nt}]'$

where $\mathbf{u}_t = (\mathbf{u}'_{1t}, \mathbf{u}'_{2t}, ..., \mathbf{u}'_{Nt})'$, and

$$\mathbf{a_0} = \begin{pmatrix} \mathbf{a}_{10} \\ \mathbf{a}_{20} \\ . \\ . \\ . \\ \mathbf{a}_{N0} \end{pmatrix}, \ \mathbf{a_1} = \begin{pmatrix} \mathbf{a}_{11} \\ \mathbf{a}_{21} \\ . \\ . \\ . \\ \mathbf{a}_{N1} \end{pmatrix}, \ \mathbf{G}_l = \begin{pmatrix} \mathbf{A}_{1l}\mathbf{W}_1 \\ \mathbf{A}_{2l}\mathbf{W}_2 \\ . \\ . \\ . \\ \mathbf{A}_{Nl}\mathbf{W}_N \end{pmatrix}, \ \mathbf{\Psi}_l = \begin{pmatrix} \mathbf{\Psi}_{1l} \\ \mathbf{\Psi}_{2l} \\ . \\ . \\ . \\ \mathbf{\Psi}_{Nl} \end{pmatrix}$$

for $l = 1, 2, ...p$. If the matrix $\mathbf{G}_0$ is invertible, then we can write (6) as:

$$\mathbf{x}_t = \sum_{l=0}^{p} \mathbf{F}_l \mathbf{x}_{t-l} + \mathbf{G_0^{-1}} \mathbf{u}_t, \tag{7}$$

where $\mathbf{F}_l = \mathbf{G_0^{-1}} \mathbf{G}_l$. The GVAR model (7) can be solved recursively and used for the impulse response function analysis.

4 Data

The analysis is carried out using both macroeconomic and bank level data on a quarterly basis covering the period 1985Q1 to 2007Q4. We do not use the post 2007 data to avoid agency problems between the borrowers and lenders, which are expected to be larger in crisis periods in comparison to the normal times. Furthermore, as the framework of monetary policy has changed substantially following the global financial crisis, it is preferable to examine the presence of risk-taking channel of monetary policy in normal conditions to capture the true relation.

Our GVAR framework utilizes bank level variables extracted from the Call Reports, available on the Federal Reserve Bank of Chicago website.[17] Using this dataset, we construct bank's total loans to total assets ratio, (tl_{it}, rcfd1400/rcfd2170).[18] We use return on assets, (q_{it}, riad4340/rcfd2170), as a performance measure. The share of nonperforming loans to total loans is our main proxy for bank risk (br_{it}). Nonperforming loans are defined as assets past due 90 days or more (rcfd1403), plus assets placed in nonaccrual status (rcfd1407).

[17] All insured banks in the US are required to submit income-statement and balance-sheet data to the Federal Reserve each quarter, which is referred to as the Call Report.

[18] The numerator measures total loans and lease financing receivables net of unearned income. The denominator is the bank's total assets.

We also used macroeconomic variables including the GDP (y_t) and real house prices (hp_t^r). Real house prices were measured as a ratio of the Freddie Mac Mortgage price to the GDP deflator. Data on house prices were extracted from FreeLunch.com. Data on the GDP deflator were obtained from Federal Reserve Bank of St. Louis.

4.1 Constructing bank level data

To carry out the investigation, we extracted bank level data from the largest 100 banks in the US given their 2007 total asset values. The analysis focused on those banks which fully contribute to the dataset for the entire period under scrutiny. We screened banks from our database if their loan to assets ratio was greater than one.[19] Furthermore, we eliminated those banks whose nonperforming loans to total loans ratio or return to asset ratio were in the bottom or the top percentile at any point in time.[20]

Our final bank level sample is comprised of 30 banks which commanded 46% of the total assets in the US banking system in 2007.[21] Figure 1 shows the ranking of the banks in the sample based on banks' total assets, where the largest bank is Bank2 and the smallest bank is Bank61. Table 1 provides some details on our bank level data. Figure 2 presents the average total loans of these banks. Given the size of total loans depicted in this figure, we deduce that some banks have a larger proportion of their assets in non-traditional bank activities. As portrayed in Figure 3, which shows the composition of loan portfolio of all banks, our sample is very heterogeneous. In fact, the theoretical literature on risk-taking channel argues that individual bank characteristics plays a significant role on the response of risk variables to monetary and other shocks.

4.2 Measuring bank risk

The risk-taking channel focuses on the incentives of banks to engage in ex-ante risky investments. Given the nature of our data, we can not distinguish new loans from outstanding loans at the time of a monetary policy shock. Hence, similar to Buch et al. (2014b), we use the share of nonperforming loans to total loans as our main proxy for bank's risk (br_{it}). This proxy informs us about changes in the overall quality of the stock of credit and allows us to scrutinize the relationship between monetary policy and the stability of the financial

[19]Twenty eight banks were not present over the entirety of our sample while three banks registered a loan to asset ratio greater than one.

[20]Thirty nine banks failed to satisfy both criteria.

[21]Overall, these banks account for 60% of the assets of the top 100 banks in the US.

intermediaries. Furthermore, this ratio is not significantly affected by the changes in the accounting standards and it can be constructed over a long time period.

We use the Z-score, as an alternative proxy for bank risk.[22] This measure can be interpreted as the distance (number of standard deviations) that a bank's profit has to fall for the bank to become insolvent. Hence, it is inversely related to the probability of insolvency: the higher the Z-score is, the more stable the bank is. This widely used risk measure is calculated as:

$$Z = \frac{ROA_{it} + CAR_{it}}{Sd(ROA_{it})}$$

where ROA is the return on assets (riad4340/rsfd2170), CAR is total equity over total assets of bank i in year t (rcfd3210/rcfd2170) and $Sd(ROA)$ is the standard deviation of return on assets. Figures 4 and 5 show the ranking of banks in our sample according to their nonperforming ratio and the Z-score, respectively. Even though the focus of each measure is different, these figures show that both measures yield a very similar ranking of banks.

4.3 Measuring monetary policy shock

One of the challenges in examining the link between monetary policy shocks and banks' risk-taking behaviour is the identification of exogenous changes in monetary policy. The use of poor proxies for monetary policy shocks would lead to biased results due to reverse causality (that future risk may imply current monetary expansions) or omitted variables as such variables, which are correlated with the stance of monetary policy, can influence risk-taking activities of banks. Although expected defaults are not explicitly included in the reaction function of central banks, they might be considered indirectly because expected economic conditions would have a direct impact on future defaults. For example, Bernanke and Gertler (1999) argue that policy rates should not respond to changes in asset prices unless they signal changes in expected inflation. Furthermore, Ioannidou et al. (2015) show that during periods of financial uncertainty central banks tend to reduce interest rates. Therefore, one should consider the endogeneity between monetary policy decision and financial uncertainty (during which the number of expected defaults increase) in an empirical investigation.

A standard approach employed in the literature to identify a monetary policy shock has been the VAR methodology. However, this methodology can be criticized in two aspects.

[22] See for example Laeven and Levine (2009), Foos et al. (2010) and Altunbas et al. (2011).

First, because policy makers have become more forward looking over the years, identification of monetary policy shocks using VAR models has become a more difficult task.[23] Furthermore, the identification problem gets worse if there is evidence of non-fundamentalness.[24] Second, Benati and Surico (2009) argue that there is a fundamental disconnect between what is a structural shock within a dynamic stochastic general equilibrium (DSGE) model and what is identified as structural in the corresponding VAR representation implied by the same DSGE model. In fact, recent research has shown that comparison of structural VAR (SVAR) estimates with those from a DSGE model is not straightforward and that caution must be exercised.[25]

The identification of monetary policy shocks becomes an even more complicated task once we consider the view that central banks have to account for future defaults. To overcome this hurdle, one can use the RR approach, which suggests regressing the intended policy rates on the Fed's forecast of inflation and real economic activity.[26] However, the RR approach assumes that the impact of forward looking variables on the central bank's reaction function remains constant across time. Yet, Barakchian and Crowe (2013), using estimates from a five-year rolling window, have shown that the $RMSE$ and R^2 figures obtained from the RR model vary significantly over the sample. Moreover, Barakchian and Crowe (2013) have demonstrated that the forward-looking variables in the RR model becomes significant only after 1988. These results suggest that a proxy which fails to capture time-variation and structural breaks in the data generation process will lead to biased estimates. Hence, rather than directly implementing the RR model, we extend it to account for time variation and endogenous regime shifts by allowing the parameters of the conditional mean to be time-varying while the variance of the error term to follow a Markov regime switching process.[27] The resulting monetary policy series are plotted in Figure 6.

[23] Barakchian and Crowe (2013) demonstrated that the Fed became more forward looking after 1988. Also see Orphanides (2003), Boivin and Giannoni (2006) and Leeper et al. (1996) on the forward looking behaviour of the Fed.

[24] A model is subject to non-fundamentalness when structural shocks can not be recovered from the current and past observations, see Hansen and Sargent (1991).

[25] For further discussion see Kilian (2013).

[26] Romer and Romer (2004) measured monetary policy shocks using a reaction function, in which the desired federal funds target rate was the dependent variable and the right-hand side variables included the level of the desired federal funds target prior to the FOMC meeting and the forecasts of 17 series (the current quarter of unemployment, eight forecasts for the real GDP growth and the GDP deflator) taken from the Greenbook.

[27] To compute the Romer and Romer (2004) type shocks, we employed approximate Maximum likelihood Estimator (MLE) as discussed in Kim (1994). For details concerning this algorithm see Kim and Nelson (1999), section 5.5.

Note that by allowing for parameters to be time-varying we account for the impact of structural breaks driven by external uncertainty. In particular, by allowing for Markov switching in the error term not only we account for the potential heteroscedasticty in the errors but we also account for the unobserved forward looking elements represented by an unobserved state variable. To that end, Jeanne and Masson (2000) argue that the unobserved state of Markov switching model reflect market expectations. In the same spirit, Davig and Leeper (2007) treat regime shifts as an ongoing process in the sense that if a regime has changed, then a regime can change again. This is because, agents form expectations to reflect the belief that a regime change is possible. Hence, expectations about regime changes will affect the agents behaviour in the current regime.[28] In our case, by allowing for time variation and regime-shifts in the standard RR model, we implicitly account for alternative sources of uncertainty that might affect the Fed's reaction function.[29]

5 Empirical analysis

In this section, we present and discuss our empirical results.[30] As a prerequisite, we start our investigation by testing the order of integration of the endogenous and exogenous variables. We then examine the endogeneity of bank specific foreign variables.[31] Next, we discuss impulse response functions of nonperforming loans to monetary policy shocks. Subsequently, we examine the spillover effects that may emerge due to global shocks or due to shocks emanating from large *versus* small banks. Lastly, we use banks' Z-score as an alternative measure of bank risk and confirm our findings.

Our GVAR model includes the following vectors of endogenous and star (exogenous) variables:

$$\mathbf{x}_{it} = [br_{it}, q_{it}, tl_{it}, y_t, hp_t^r],$$

$$\mathbf{x}^*_{it} = [br^*_{it}, q^*_{it}, tl^*_{it}, rr_t]$$

[28]Davig and Leeper (2007) argue that ongoing regime changes form expectations that can affect the response of inflation and output to exogenous shocks. Extending the Taylor's principle by allowing the parameters to follow a Markov process, they show that a change from an active to a passive monetary policy can affect the equilibrium under the former regime in two important ways. First, if the passive regime is sufficiently passive or persistent, then multiple equilibrium can arise. Second, even in a determinate equilibrium the possibility of switching to a dovish regime can raise aggregate volatility.

[29]Appendix B presents our extension to the RR approach.

[30]Empirical results are obtained using the GVAR toolbox provided by Smith and Galesi (2014).

[31]Results for the unit root, endogeneity test and other statistics concerning the relationship between domestic and foreign variables (i.e. elasticities and pairwise correlation) are provided in Appendix C.

where, br_{it}, q_{it}, tl_{it}, y_t, hp_t^r denote bank risk, return on assets, total loans to assets, output growth and real house prices, respectively. The corresponding exogenous foreign specific variables and the monetary policy shock are given by br_{it}^*, q_{it}^*, tl_{it}^* and rr_t, respectively. Note that by construction, monetary policy shocks (rr_t) are assumed to be exogenous. Furthermore, based on the estimation of $VARX^*(p_i, q_i)$, the null hypothesis of exogeneity for all variables in $\mathbf{x}_{it}^*$ are confirmed.

6 Impulse response function analysis

In what follows, we simulate the following innovations: 1) the impact of an expansionary monetary policy shock on banks' nonperforming loans and return on assets; 2) the impact of a negative global shock on banks' nonperforming loans; 3) the impact of a negative shock that emanates from a large and a small bank on the rest of the banks' in the system. Results from banks' Z-score, as an alternative proxy for risk-taking behaviour, confirm our findings.

6.1 Impulse response to an expansionary monetary policy shock and bank heterogeneity

Here, we focus on the effect of a negative interest rate shock (expansionary monetary policy) to scrutinize banks' risk-taking behaviour. In doing so we examine the effect of a downward movement in policy rate rather than an upward movement, because bank risk is more sensitive to expansionary monetary policy shocks (see Lopez et al., 2011). In what follows, we investigate the behavior of banks' nonperforming loans and confirm our observations by examining movements in banks' Z-score in response to an expansionary monetary policy shock.

Response of nonperforming loans

Figure 7 shows that, in the short-run, nonperforming loans of all banks generally decline in response to a downward one standard deviation shock to monetary policy. However, this initial response reverses in the medium-run as nonperforming loans begin to increase for most banks. In particular, banks' nonperforming loans, i.e. bank risk, increase after the fourth quarter following the expansionary monetary policy shock. This reversal is considered as evidence in favour of the risk-taking channel (see, for example, Altunbas et al., 2011).

The dynamics of nonperforming loans can be explained as follows. Following an expansionary monetary policy shock, banks extend credit to credit worthy as well as risky borrowers, as the collateral and asset values of potential borrowers increase. In the short-run, all new borrowers are expected to pay the interest charge on the loans given the low rates. As a result, a drop in nonperforming loans is expected when the interest rate declines due to the reduction of the interest burden on existing borrowers. However, in the long-run, as interest rates increase, coupled with the competitive nature of the business environment, a fair number of riskier borrowers could fail to comply with their commitments and render an increase in nonperforming loans. In fact this is what we observe in Figure 7.

The reaction of nonperforming loans to the monetary policy shock varies across banks. Dell'Ariccia et al. (2017) argue that in the medium- to long-run, the response of bank risk to a monetary policy shock is driven by two countervailing forces, which are related to the bank's capital structure. In particular, due to limited liability there is the risk-shifting effect, which increases the probability of monitoring after a decrease of the policy rate. Alternatively, there is the pass-through effect, which decreases the incentive to monitor due to declining profits following a decrease in the lending rate. The relative strength of these two forces depend on the extent of bank capitalization. For low level of capitalisation the former will dominate the latter effect and lead to a lower level of nonperforming loans. This is because low policy rates will increase the intermediation margin. Thus, banks with high levels of leverage have an incentive to increase monitoring to realize expected returns from higher margin. However, for banks with high levels of capital, the pass-through effect will dominate leading to an increase of nonperforming loans. In the light of this discussion, banks with higher deposits in their capital structure are expected to yield low risk (for instance Bank2, Bank13, Bank26, Bank33 and Bank61), whereas, banks with high equity to capital ratio (for instance Bank5 and Bank7) would exhibit stronger movements in their nonperforming loans. Figure 8 plots banks' average equity capital ratios.

Response of return on assets

A related problem is the evolution of return on assets as monetary policy changes. Figure 9 depicts the response of banks' return on assets to an *expansionary* monetary policy shock. We find that banks' return on assets would increase in the short-run but fall in the medium horizon. This is consistent with the results observed in Figure 7 where nonperforming loans decrease in the short-run but increase in the medium-run. As a consequence, return on assets increases initially, as nonperforming loans decline. However, in the medium-run, as nonperforming loans increase, return on assets declines.

Recall that, through a negative change of the policy rate, the policymakers' aim is to achieve higher economic growth and lower unemployment by inducing businesses to increase their fixed investment expenditures. However, our examination show that expansionary monetary policy shocks can introduce a certain fragility into the financial system evidenced by declining return on assets and increasing nonperforming loans in the medium- to the long-run. This observation is in contrast with the initial objectives of the policy makers and suggestive for the prevalence of the risk-taking channel.

6.2 Spillover effects: Global *versus* bank specific shocks

An important question is whether there is evidence of spillover effects of credit risk within the banking system. To examine the spillover effects we took two routes. Initially, following Dees et al. (2007), we generated a global bank risk shock, which is defined as the weighted average of specific shocks across all banks and examined its impact on nonperforming loans of individual banks. Results, which are available upon request, do not provide clear evidence of spillover effects due to global shocks. For some banks there is evidence that the risk is increasing but for some others we find no such effects.

In contrast, when we investigate the impact of an adverse shock emanating from an individual bank to the rest of the system, we find evidence that risk could spillover through the financial system. To that end, we provide details for the case of a shock that emanated from a large bank, Bank3, and that from a small bank, Bank61. It should be noted that in terms of assets, Bank3 is on average ten times larger than Bank61. Furthermore, based on the Z-score and nonperforming loans, it turns out that Bank3 is one of the riskiest bank whereas Bank61 can be considered as one of the least risky bank in our sample.

Figures 10 and 11 portray the response of banks to a positive shock to the nonperforming loans of Bank3 and Bank61 (i.e. large and small banks), respectively.[32] Figure 10 shows that the nonperforming loans of banks increase significantly when an adverse shock emanates from Bank3.[33] In contrast, Figure 11 provides evidence that the remaining banks in the

[32]We identify shocks using the orthogonalization scheme suggested by Dees et al. (2007). In particular, a recursive identification scheme is adopted based on bank size where small banks are preceded by large banks.

[33]The magnitude of the response is not homogeneous across all banks, some banks show a strong and significant response while others show a mild but long lasting response. In some cases nonperforming loans decrease after about a year.

system are not affected significantly when a similar type of shock emanates from Bank61.

The presence of spillover effects from a large and risky bank to the rest of the banks should be of concern to the policy makers. Given our findings, there is a firm basis for regulators and policy makers to closely monitor large banks, as managers' of larger banks may have the tendency to approve loans to riskier borrowers. Were the interest rates to increase unexpectedly, these banks can easily end up with substantial amounts of nonperforming loans, affecting the whole banking sector. Furthermore, if these banks are considered to be *too big to fail*, their managers would not refrain from lending to riskier borrowers in search for higher yield when they believe that the bank would be rescued by the Fed. As a consequence, risk-taking behaviour of large risky banks could ultimately yield a financial system which is open to systemic failures.

6.3 Sensitivity analysis

To check the robustness of our findings, we repeated the analysis using banks' Z-score as an alternative measure of risk and obtained similar results. In particular, Figure 12 plots the response of the Z-score to an *expansionary* monetary policy shock. The figure depicts an immediate and significant decline of the Z-score (including banks Bank2, Bank7, Bank19, Bank53 among others) following the monetary policy shock, and provide support in favor of the risk-taking channel. Interestingly, the Z-score also increases for four of the banks in the sample (i.e., Bank13, Bank25, Bank30 and Bank58), suggesting that bank risk for these institutions declines when the monetary policy is relaxed. Among these four banks, only Bank13 is relatively large.

When we use banks' Z-score to examine the spillover effects, our results remain similar to our earlier findings. Figure 13 plots the impulse responses of banks' Z-score to a shock emanating from Bank3 (large bank). Here, we observe that bank risk increases for a large fraction of banks (the Z-score declines). Figure 14 displays the results of the same experiment for the smallest bank (Bank61) as the source of the shock. In this case, we do not observe a significant response from any bank. We would like to note that we also investigated the impact of an adverse shock to Bank13's Z-score and found that it did not have any impact on the rest of the banks in our system. This is in line with our prior expectations. Although relatively large, Bank13 has a low risk structure. Results for this experiment are available upon request.

7 Conclusion

In this study, we use the GVAR framework to investigate three interrelated questions concerning the risk-taking channel of the monetary transmission mechanism. We examine the impact of a downward exogenous change of policy rate on banks' risk-taking activities. We scrutinize whether banks' risk taking behaviour is homogeneous. Lastly, we examine whether there are spillover effects due to global and bank specific shocks.

Our investigation, based on a panel of large US banks, provides evidence of an active risk-taking channel in the US. In particular, we show that banks' risk-taking behaviour is more pronounced for large, well capitalized banks; an observation consistent with Dell'Ariccia et al. (2017) who discuss the role of capital structure in relation to banks' risk-taking behaviour. Lastly, we provide evidence that shocks originating from larger and riskier banks have lasting effects on the whole system, while shocks from smaller and less risky banks do not. Our investigation also yields that global shocks do not lead to spillover effects in our system. The results are robust to the use of banks' nonperforming loans and Z-score as alternative risk measures.

Our findings are relevant and important to both monetary policy authorities and academic circles. Given that standard monetary policy rules ultimately affect the financial markets through several drivers such as credit, liquidity and risk taking, we argue that policy makers should not ignore but monitor the stability of the financial intermediaries. In fact, as the debate goes on, many countries which were effected by the global financial crisis have already begun to implement macroprudential policies to prevent the build up of financial imbalances and to ensure that the financial system is resilient to shocks. More research along these lines is needed.

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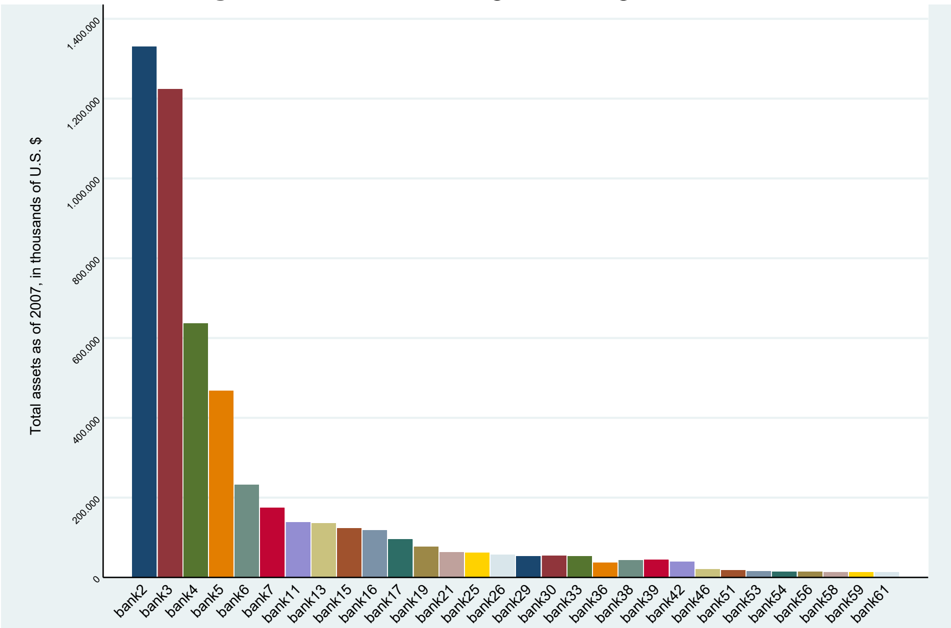
8 Tables and Figures

Table 1: Summary information

Name of the Bank	Bank's ID	Rank	Consolidated Assets	Domestic Assets(%)	Domestic Branches	Foreign Foreign
JPMORGAN CHASE BK NA	852218	2	1,179,390	652,824(55)	2852	46
CITIBANK NA	476810	3	1,019,497	537,86(53)	1005	375
WACHOVIA BK NA	484422	4	518,123	487,894(94)	3159	11
WELLS FARGO BK NA	451965	5	398,671	398,546(100)	4052	2
U S BK NA	504713	6	217,802	216,581(99)	2822	1
SUNTRUST BK	675332	7	182,628	182,628(100)	1942	0
NATIONAL CITY BK	259518	11	134,345	133,894(100)	1468	2
STATE STREET B & TC	35301	13	96,296	82,651(86)	2	10
PNC BK NA	817824	15	90,142	88,357(98)	953	0
KEYBANK NA	280110	16	88,081	85,863(97)	1158	1
BANK OF NY	541101	17	85,952	52,731(61)	8	9
CITIBANK SD NA	486752	19	79,761	79,761(100)	0	0
COMERICA BK	60143	21	58,543	57,252(98)	382	1
FIFTH THIRD BK	723112	25	52,672	52,672(100)	415	1
NORTHERN TC	210434	26	52,313	33,358(64)	17	3
FIFTH THIRD BK	913940	29	48,441	48,441(100)	718	0
M & I MARSHALL	983448	30	48,017	48,017(100)	309	0
COMMERCE BK NA	363415	33	41,170	41,170(100)	343	0
FIRST HORIZON NAT CORP	485559	36	37,608	37,608(100)	222	0
HUNTINGTON NB	12311	38	34,914	34,914(100)	491	0
COMPASS BK	697633	39	34,181	34,181(100)	444	0
MELLON BK NA	934329	42	26,226	22,713(87)	26	1
ASSOCIATED BK NA	917742	46	20,532	20,532(100)	351	0
ZIONS FIRST NB	276579	51	14,849	14,848(100)	169	0
CITY NB	63069	53	14,665	14,665(100)	72	0
BANK OF OK NA	339858	54	14,366	13,766(96)	79	0
COMMERCE BK NA	601050	56	13,891	13,891(100)	169	0
FIRST-CITIZENS B & TC	491224	58	13,327	13,327(100)	334	0
FROST NB/CULLEN	682563	59	13,307	13,307(100)	123	0
VALLEY NB/VALLEY NBC	229801	61	12,364	12,364(100)	161	0

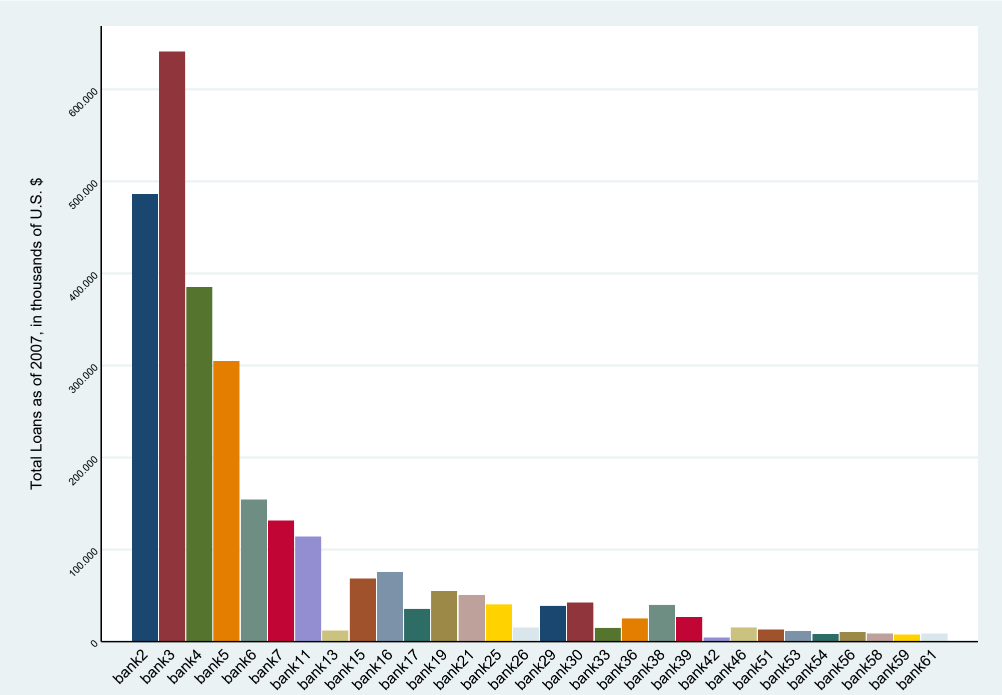
Notes: The table shows information about the 30 banks used in this paper as of 2007. The ranking is based on total assets. Assets are in thousands of U.S.$. Data are from The Federal Reserve System, see https://www.federalreserve.gov/releases/lbr/.

Figure 1: Banks' Ranking According to Assets Size



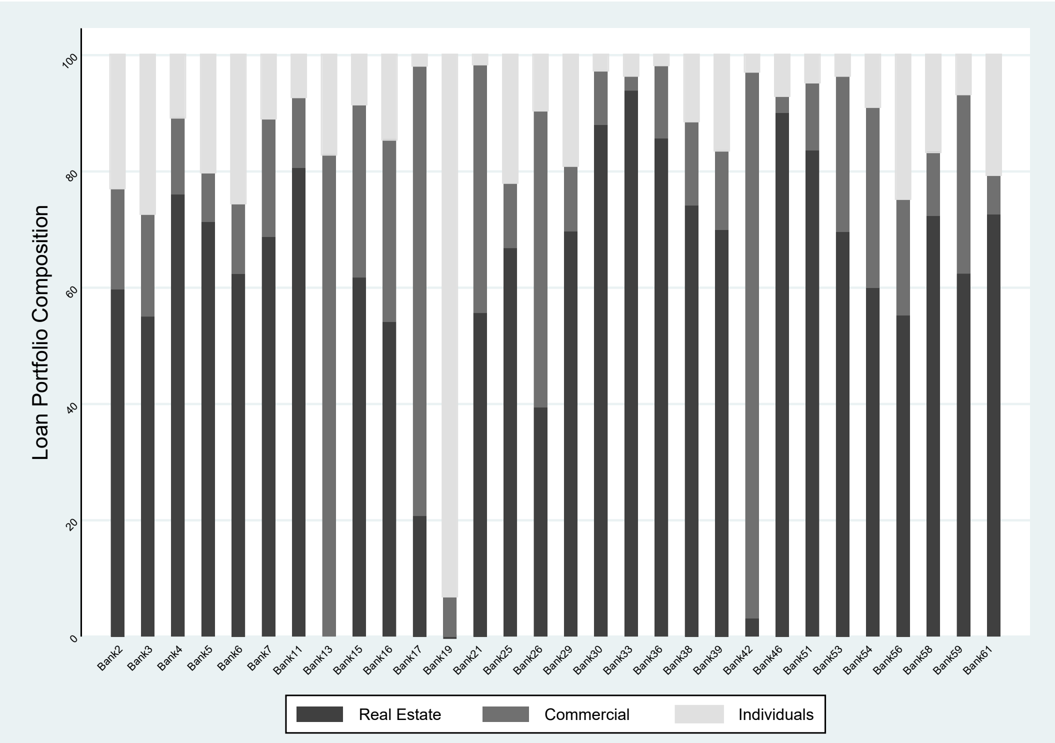
Notes: The figure shows ranking of the 30 banks used in the analysis with respect to banks' 2007 asset size. The figure is constructed using "rcfd2170" call report item.

Figure 2: Banks' Average Total Loans



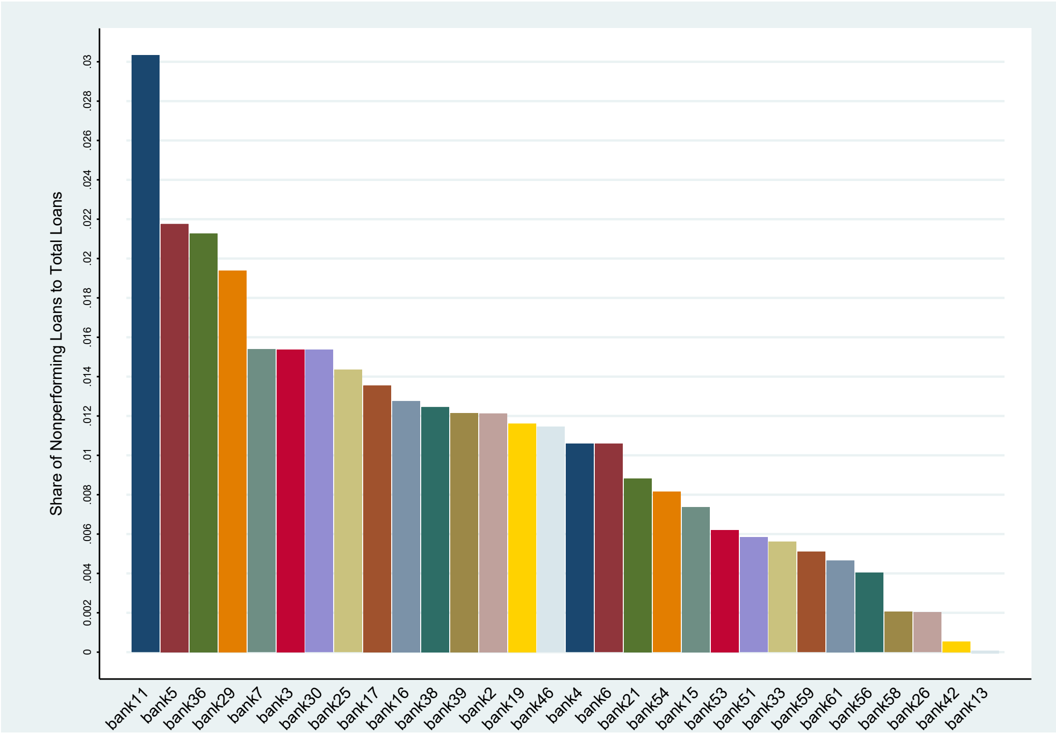
Notes: The figure shows the average total loans of the 30 banks over the sample period, 1985Q1 to 2007Q4. The figure is constructed using "rcfd1400" call report item.

Figure 3: Banks' Total Loan Composition



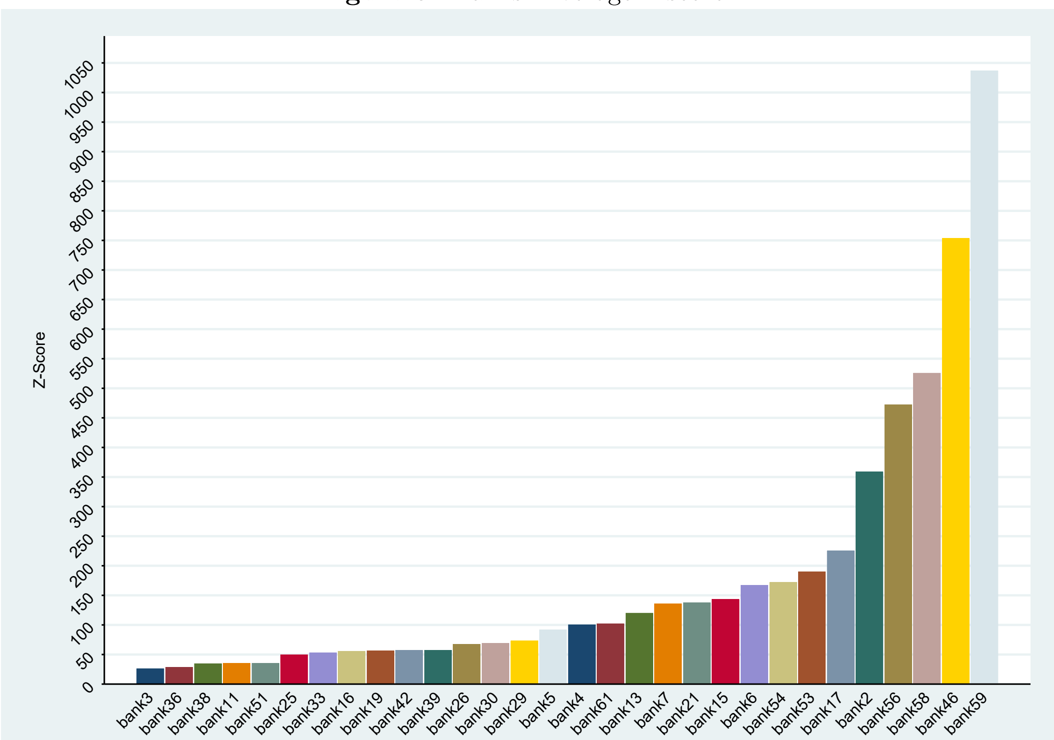
Notes: The figure shows the composition of the loan portfolios of the 30 banks used in the paper. The figure represents the average of each component over the sample period, 1985Q1 to 2007Q4. The figure is constructed using: "rcfd1975" to capture loans to individuals, "rcfd1600" to capture commercial and industrial loans and "rcfd1410" to capture loans secured by real estate.

Figure 4: Banks' Average Nonperforming Loans Ratio



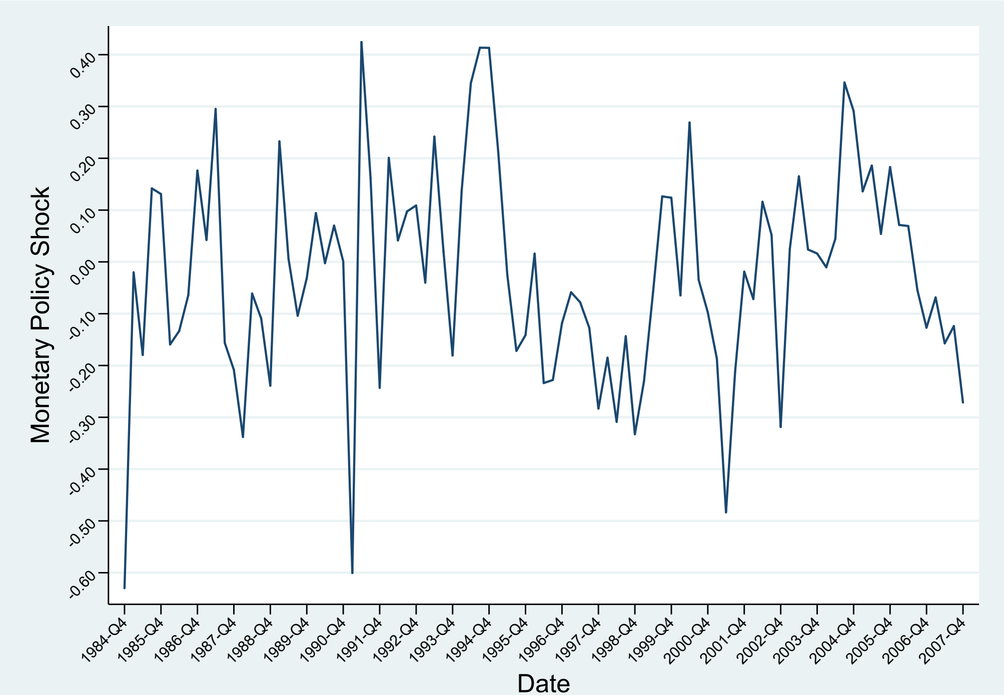
Notes: The figure shows the ranking of the average nonperforming loans ratio of the 30 banks used in the paper over the sample period, 1985Q1 to 2007Q4. The figure is constructed using: "rcfd1400" to capture total loans and "rcfd1407+rcfd1403" to capture total nonperforming loans.

Figure 5: Banks' Average Z-score



Notes: The figure shows the average Z-score of the 30 banks used in the paper over the sample period, 1985Q1 to 2007Q4. The figure is constructed using: "riad4340" to capture net income, "rsfd2170" to capture total assets and "rcfd3210" to capture total equity capital.

Figure 6: Monetary Policy Shock Measure



Notes: The figure plots the Romer and Romer (2004) based monetary policy measure accounting for time variation and endogenous regime shifts by allowing the parameters of the conditional mean to be time-varying while the variance of the error term to follow a Markov regime switching process. The sample period is, 1985Q1 to 2007Q4.

Figure 7: Response of Nonperforming Loans To a Negative Shock in Interest Rate

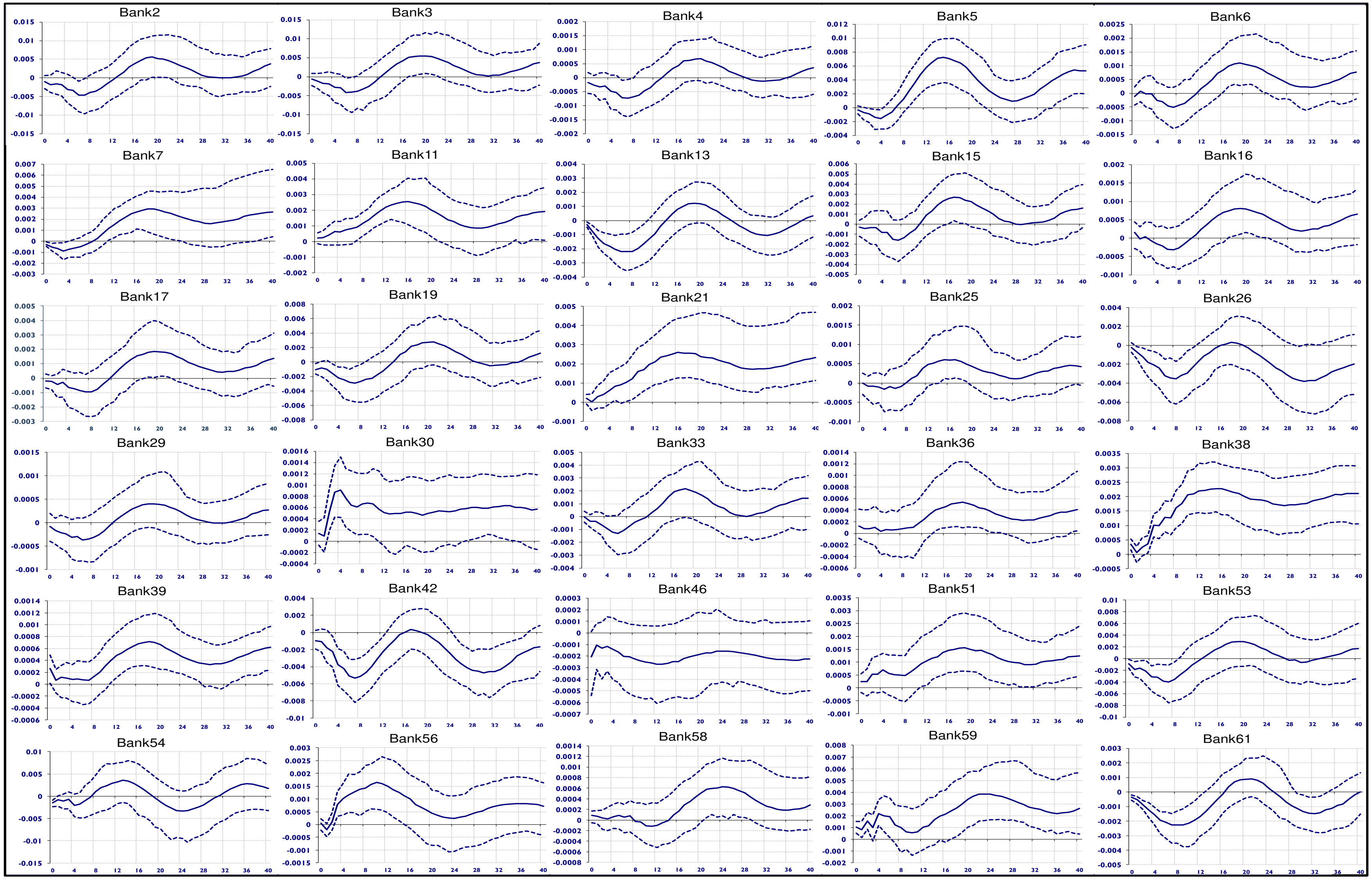
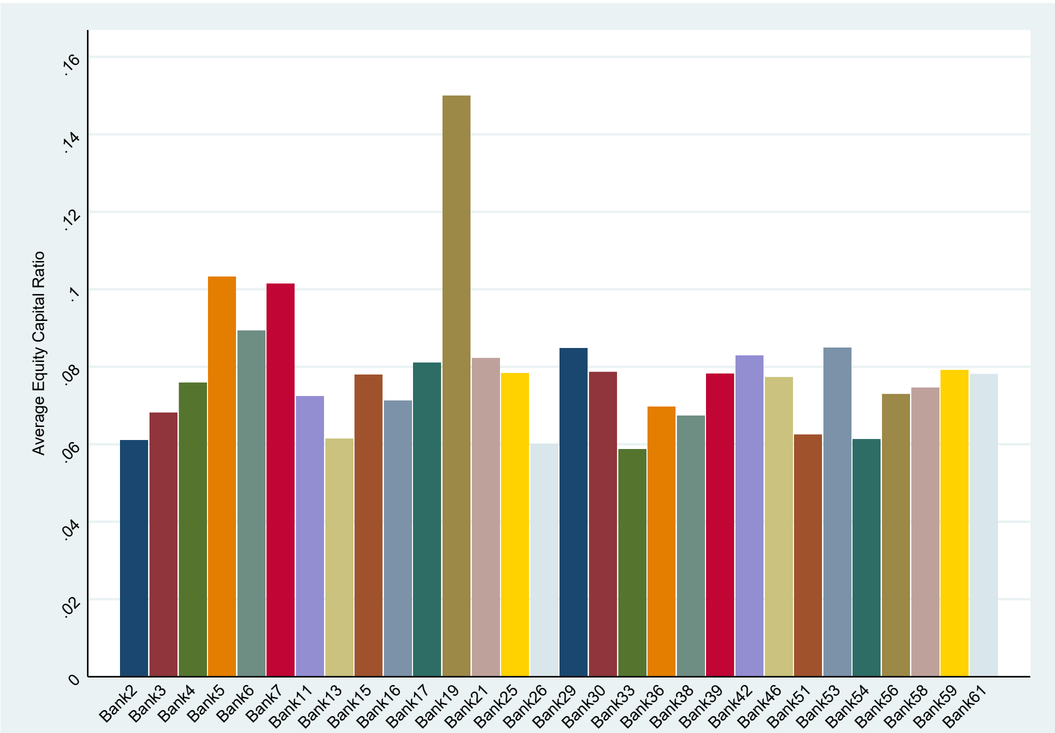


Figure 8: Average Equity to Capital Ratio



Notes: The figure shows the average equity to capital ratio of the 30 banks used in the paper over the sample period, 1985Q1 to 2007Q4. The figure is constructed using: "rcfd1400" to capture total loans and "rcfd1407+rcfd1403" to capture total nonperforming loans.

Figure 9: Response of Return on Assets To a Negative Shock in Interest Rate

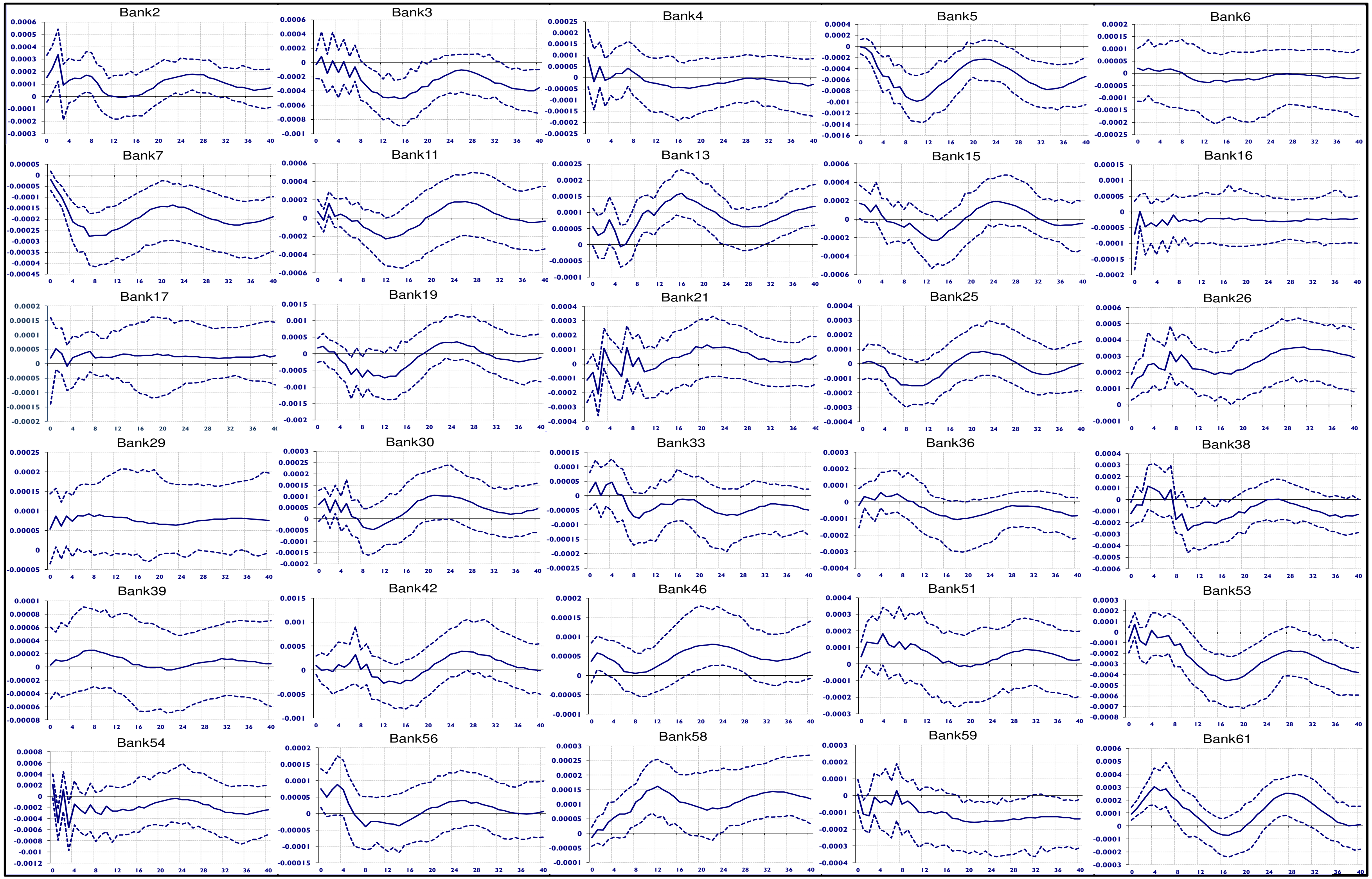


Figure 10: Response of Nonperforming Loans To a Negative Shock in Bank3 nonperforming Loans

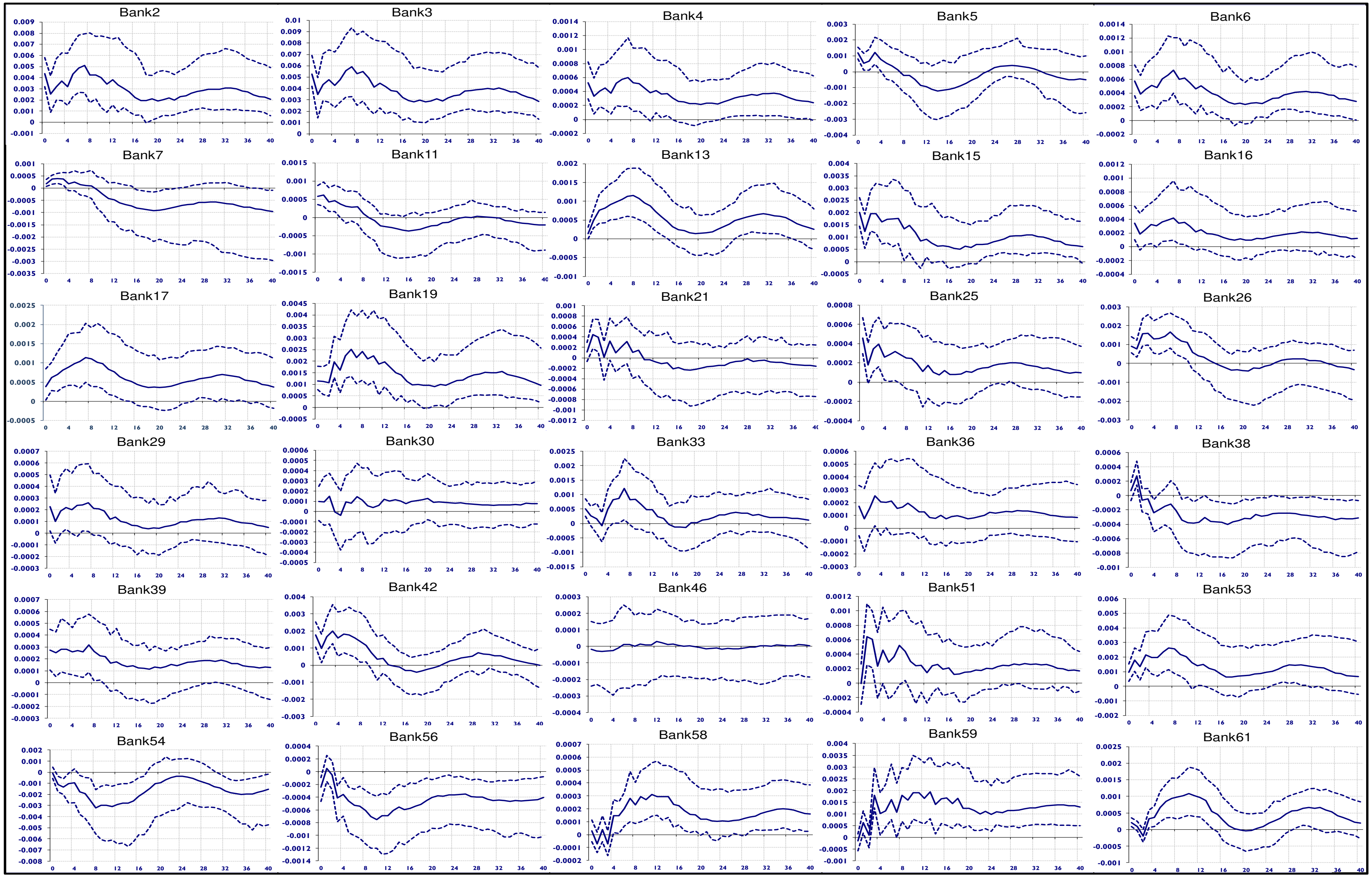


Figure 11: Response of Nonperforming Loans To a Negative Shock in Bank61 nonperforming Loans

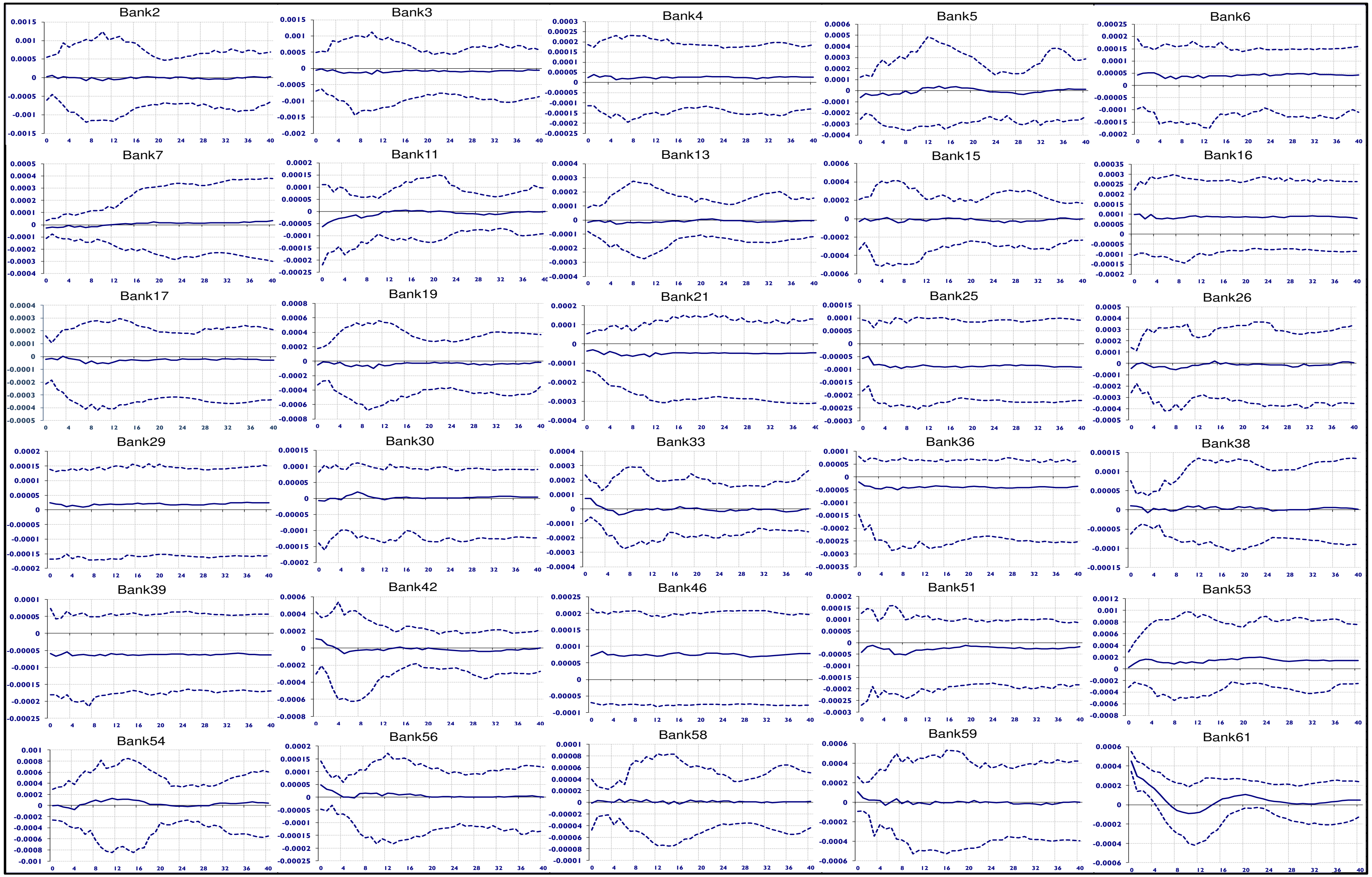


Figure 12: Response of Banks' Z-score To a Negative Shock in Interest Rate

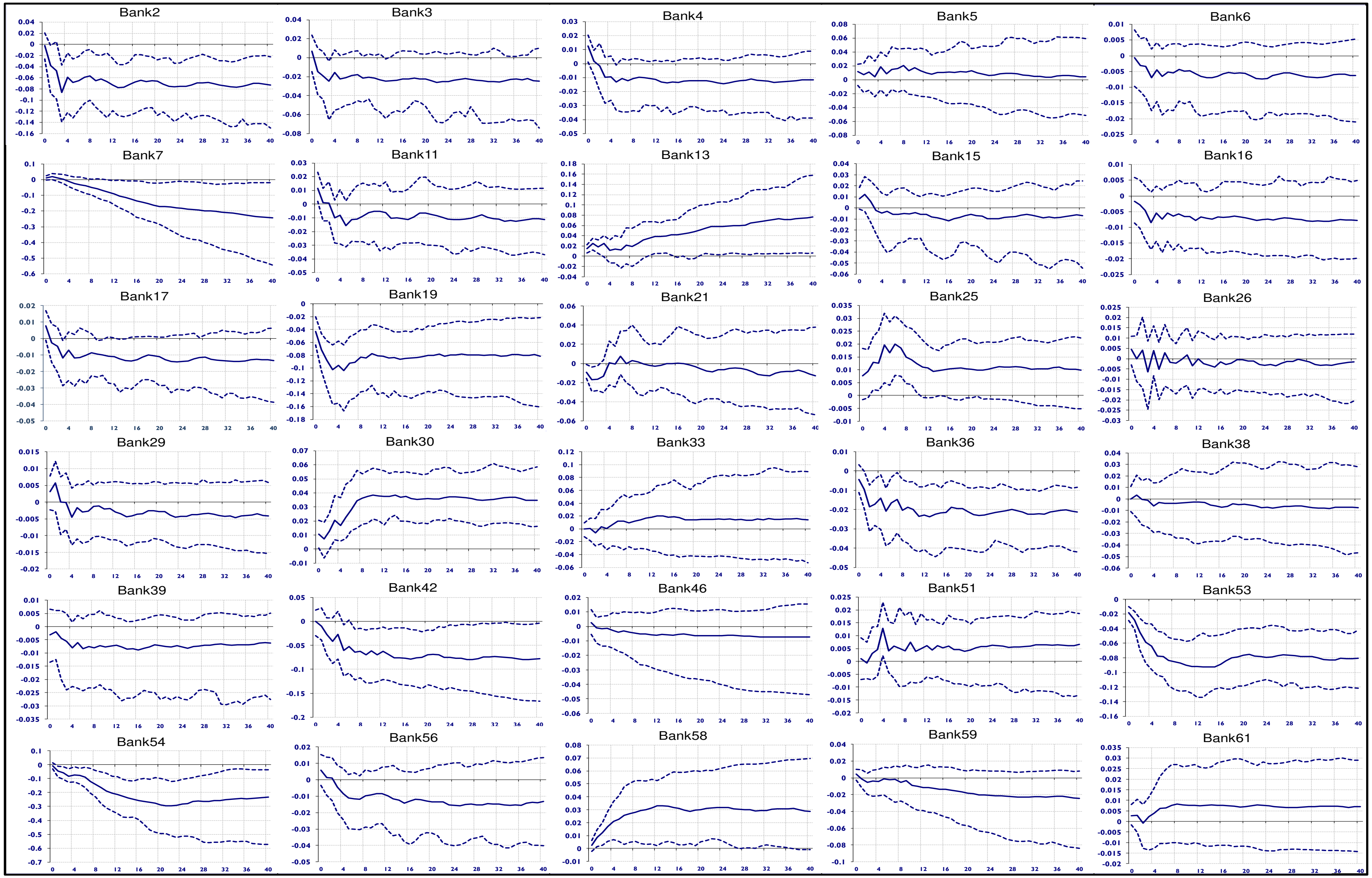


Figure 13: Response of Banks' Z-score To a Negative Shock in Bank3 Z-score

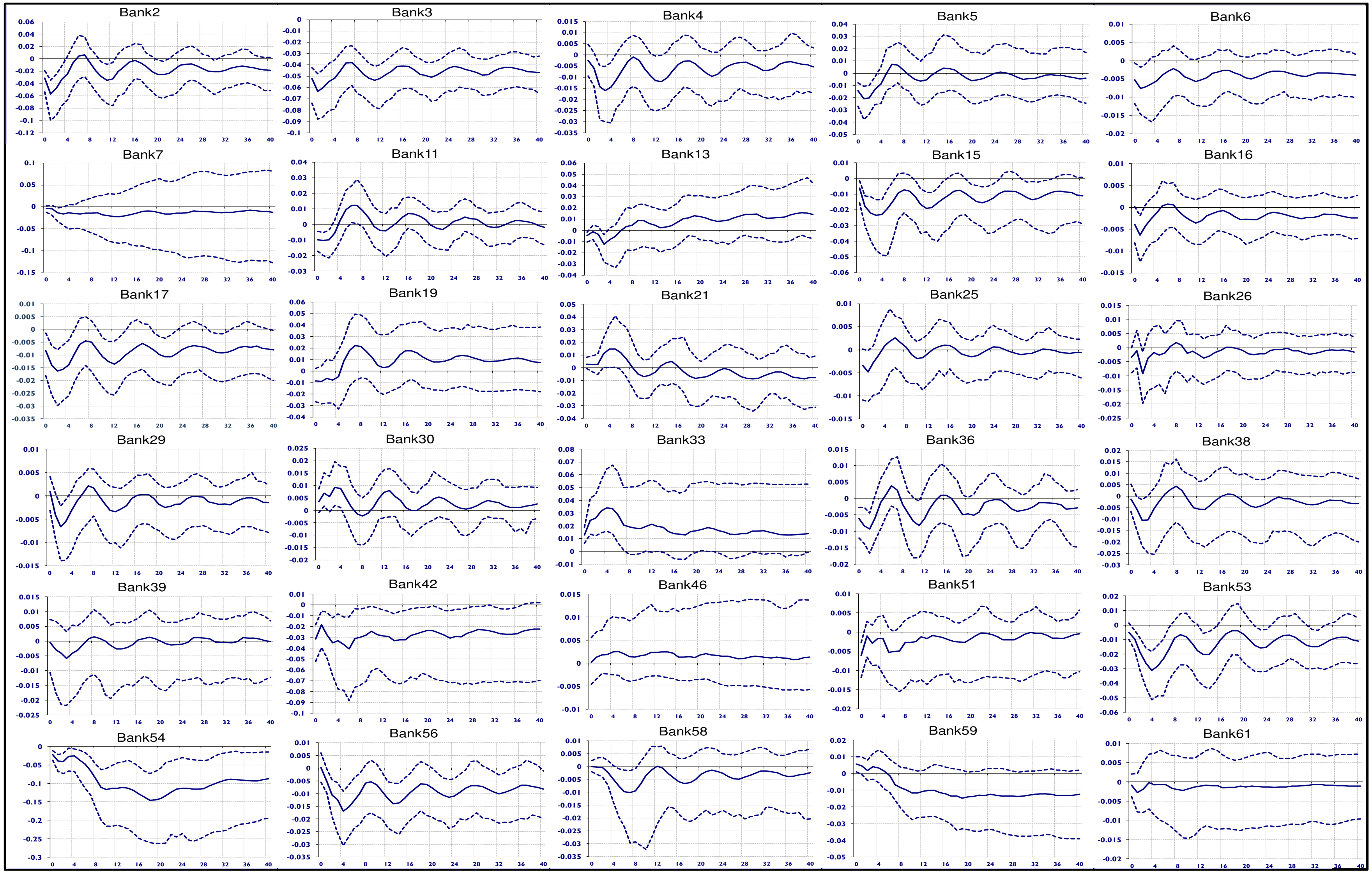
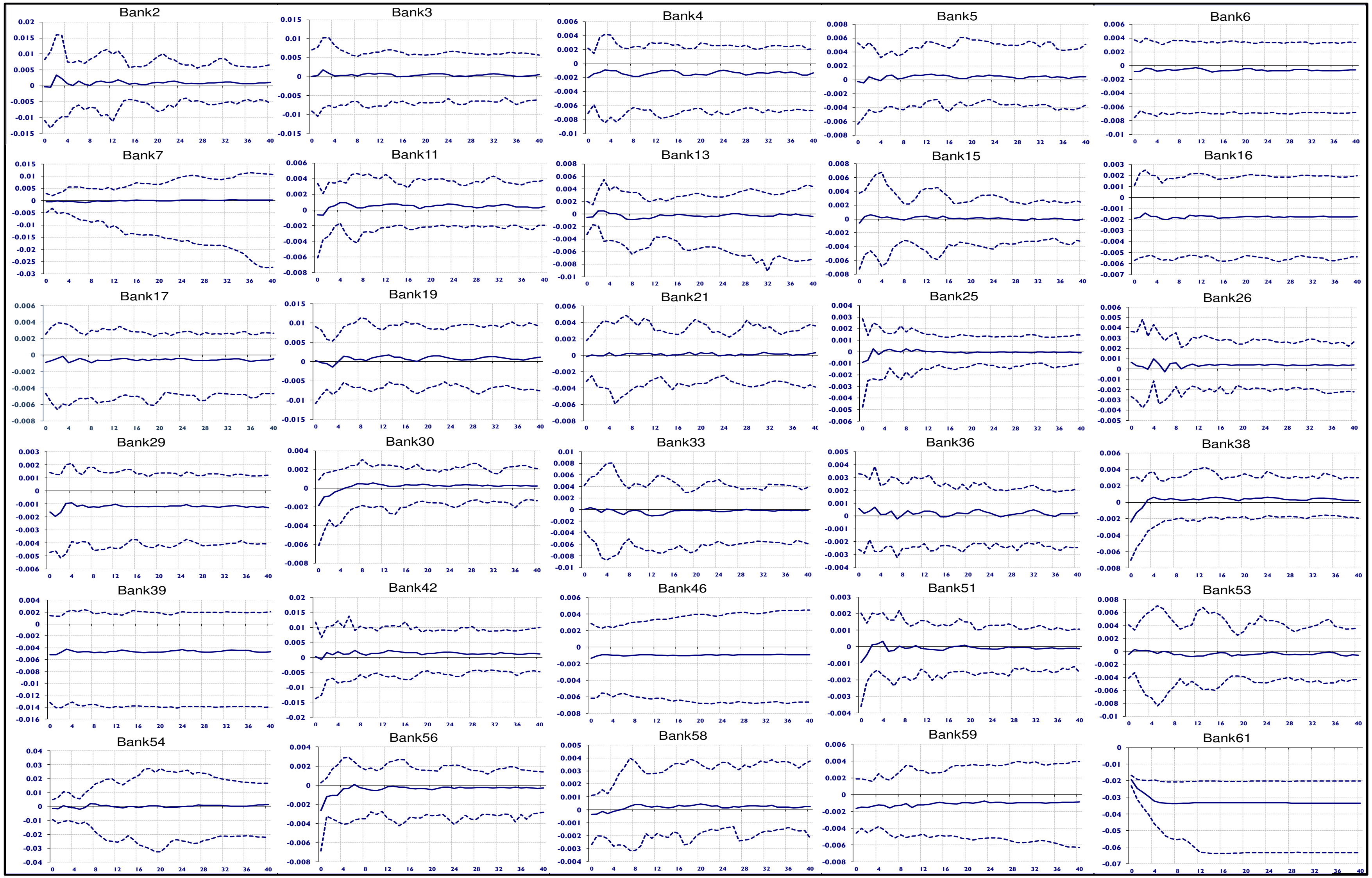


Figure 14: Response of Banks' Z-score To a Negative Shock in Bank61 Z-score



9 Appendices

Appendix A: Estimating Bilateral Exposure with Incomplete Information

For a system of N banks we are aiming to estimate a matrix of the form:[1]

$$\mathbf{X} = \begin{array}{c} \left[\begin{array}{ccccc} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,N} \\ & & \cdot & & \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,N} \\ & & \cdot & & \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,N} \end{array}\right] \begin{array}{c} a_1 \\ \cdot \\ a_i \\ \cdot \\ a_N \end{array} \\ \begin{array}{ccccc} l_1 & \cdots & l_j & \cdots & l_N \end{array} \end{array}$$

where x_{ij} denotes outstanding loans made by bank i to bank j, $a_i = \sum_j x_{i,j}$ and $l_j = \sum_i x_{i,j}$ are respectively, bank i's interbank total assets and liabilities.[2] In general, since one can only observe each bank's total interbank debt (l_j) and credits (a_i) further restrictions are required in order to identify bilateral bank exposure (x_{ij}). In the absence of any further information, a sensible approach suggested by the literature is to assume that banks maximise the uncertainty of their interbank activity. This implies that the amount lend by bank i to bank j, is increasing in both bank i's share of total lending and of bank j's share of total borrowing. Normalizing $\sum_{i=1}^{N} a_i = \sum_{j=1}^{N} l_j = 1$, the individual exposure will be given by $x_{ij} = a_i l_j$. In this specification, exposures reflect the relative importance of each institution in the interbank market.

Note, the above problem doesn't account for the restriction that a bank can not be exposed to itself. However, it is straightforward to impose the restriction that the diagonal elements of $\mathbf{X}$ are equal to zero. Given an initial estimate of $\mathbf{X}^0$, one can solve a minimisation problem to find a matrix $\mathbf{X}$ as close as possible to $\mathbf{X}^0$ subject to row and column adding up restrictions (i.e. $a_i = \sum_j x_{i,j}$ and $_j = \sum_i x_{i,j}$).[3] A suitable distance measure for this type of problem is the cross-entropy between two matrices (see Fang et al., 2012). Following this approach the appropriate interbank structure is given by the solution to:

$$\min \sum_{i=1}^{N} \sum_{j=1}^{N} x_{ij} \ln \left(\frac{x_{ij}}{x_{ij}^0} \right)$$

[1] $\mathbf{X}$ contains N^2 while the a and l provides $2N$ pieces of information. Therefore, identification of X will require $N(N-2)$ restrictions on $\mathbf{X}$.

[2] Note that a_i is computed by summing across row i while summing down across column j gives l_j.

[3] The elements of $\mathbf{X}^0$ are given by

$$x_{ij}^0 = \left\{ \begin{array}{c} 0 \text{ if } i = j \\ a_i l_j \text{ , otherwise} \end{array} \right\}$$

subject to

$$\sum_{i=1}^{N} x_{ij} = l_j$$

$$x_{ij} \geq 0$$

Note also that $x_{ij} = 0$ if, and only if $x_{ij}^0 = 0$, and $ln(0/0) = 0$. This sort of problem is solved numerically by using RAS algorithm.[4]

Appendix B: Romer and Romer (2004) Approach

Romer and Romer (2004) estimate the following model to derive a proxy for monetary policy shocks:

$$\begin{aligned} \Delta ff_m = &\alpha + \beta ffb_m + \Sigma_{i=-1}^{2}\gamma_i\Delta y_{mi} + \Sigma_{i=-1}^{2}\lambda_i(\Delta y_{mi} - \Delta y_{m-1,i}) \\ &+\Sigma_{i=-1}^{2}\varphi_i\pi_{mi} + \Sigma_{i=-1}^{2}\theta_i(\pi_{mi} - \pi_{m-1,i}) + \rho u_{m0} + \varepsilon_m \end{aligned} \tag{1}$$

where Δff_m is the change in the desired funds rate around the FOMC meeting at date m. The level of the desired fund rate before any change related to meeting is denoted by ffb_m. The forecast of inflation, real GDP growth and the unemployment rate are depicted as π, Δy and u. The subscript i refers to the forecast horizon: -1 is the previous quarter, 0 is the current quarter, 1 is the next quarter and 2 is two quarters ahead. We extent the RR approach by allowing the estimated parameters in (1) to be time-varying.[5] In particular, we write (1) in a state-space form as follows:

$$y_t = X_t'\xi_t + e_t,\ \ e_t \sim N(0, \sigma_e^2) \tag{2}$$

$$\xi_t = F\xi_{t-1} + v_t,\ \ v_t \sim N(0, Q_t) \tag{3}$$

where $y_t = \Delta ff_m$, $X_t' = [ffb_m, \Delta y_{mi}, (\Delta y_{mi} - \Delta y_{m-1,i}), \pi_{mi}, (\pi_{mi} - \pi_{m-1,i}), u_{m0}]$, and $\xi = [\alpha, \beta, \gamma_i, \lambda_i, \varphi_i, \theta_i, \rho]$ for $i = -1, 0, 1, 2$. Equations (2) and (3) are the measurement and transition equation of (1). The Kalman filter is then applied to make inferences on the changing regression coefficients ξ_t. The Kalman filter gives insights into how a rational agent updated his estimates of the coefficients in a Bayesian context with the arrival of new information in a world of uncertainty, especially under changing policy.

Note that the conditional variance of (2) consists of filter uncertainty and uncertainty concerning the future shocks:

$$f_{t|t-1} = X_t P_{t|t-1} X_t^{'} + \sigma_e^2 \tag{4}$$

where $P_{t|t-1}$ represents filter uncertainty conditional on information up to time $t-1$ and σ_e^2 represents uncertainty concerning the future exogenous shocks. To account for potential heteroscedasticity of the exogenous uncertainty we estimate a model where e_t follows a

[4] For further details see Censor and Zenios (1997).

[5] Kim and Nelson (2001), based on stability test results on the regression coefficients, consider a time-varying parameter model for the U.S. monetary growth function.

Markov process. Therefore, the version of model (2) and (3) with switching effects takes the following form:

$$e_t \sim N(0, \sigma^2_{e,S_t}) \tag{5}$$

$$\sigma^2_{e,S_t} = \sigma^2_0 + (\sigma^2_1 - \sigma^2_0)S_t, \ \sigma^2_1 > \sigma^2_0 \tag{6}$$

To estimate the model given by equations 2-6, we employ Kim (1994) algorithm.

Appendix C: Preliminary Analysis of GVAR model

C1: Unit root test

The estimation of each conditional $VARX$ model is based on the assumption that the variables included in these models are integrated of order one. We test all variables included in the GVAR model for unit root using the weighted-Symmetric Augmented Dickey-fuller (WS ADF) test introduced by Park and Fuller (1995).[6] The unit-root test results suggest that we cannot reject the hypothesis of a unit root for most of the variables.[7] We also find that the global variables and output are both integrated of order one.[8]

C2: Exogeneity test

A vital assumption in the estimation of individual bank $VARX^*(p_i, q_i)$ model is the weak exogeneity of bank specific foreign variables ($\mathbf{x}^*_{it}$). The weak exogeneity assumption in the context of a cointegrating model implies that there is no long-run feedback from bank-specific domestic variables ($\mathbf{x}_{it}$) to the bank-specific foreign variables ($\mathbf{x}^*_{it}$), without ruling out any lagged short-run feedback between the two sets of variables. If the weak exogeneity assumption is not rejected then $\mathbf{x}^*_{it}$ is said to be a "long-run forcing" for $\mathbf{x}_{it}$, which implies that the disequilibrium errors do not have any information about the marginal distribution of $\mathbf{x}^*_{it}$. A formal test for the weak exogeneity of bank-specific foreign variables is implemented by testing the joint significance of the estimated error correction terms in the marginal models of the foreign variables. In particular, for each variable ℓ of $\mathbf{x}^*_{it}$ the following regression is carried out:

$$\begin{aligned}\Delta x^*_{it,\ell} = c_{i0,\ell} + \sum_{j=1}^{r_i} \delta_{ij,\ell} ECM^j_{i,t-1} + \sum_{s=1}^{p^*_i} \phi_{is,\ell} \Delta \mathbf{x}_{it-s} + \\ \sum_{s=1}^{q^*_i} \theta_{is,\ell} \Delta \mathbf{x}^*_{it-s} + \sum_{j=0}^{j=1} \psi_{ij,\ell} \Delta \mathbf{d}_{t-j} + u_{it,\ell},\end{aligned} \tag{7}$$

where $ECM_{ij,t-1}$, $j = 1, 2, ...r_i$, are the estimated error correction terms associated with r_i cointegrating vectors found for bank i. In equation (7) p^*_i and q^*_i are the orders of lagged

[6] Note that Leybourne et al. (2005) and Pantula et al. (1994) show that the WS ADF test outperforms both the traditional ADF and the GLS-ADF test proposed by Elliot et al. (1996).

[7] We also carried out the Augmented Dickey-fuller (ADF) test. Results from these tests are similar and are available upon request.

[8] Test results are available from the authors upon request.

changes of domestic and foreign variables; $(\mathbf{x}_{it})$ and $(\mathbf{x}^*_{it})$, respectively.[9] The test for weak exogeneity is an F-test of the joint hypothesis that $\delta_{ij,\ell} = 0$, for $j = 1, 2, ..., r_i$ in (7). The F-test results, which we summarize in Table D1, Appendix D, show that the weak exogeneity assumption is not rejected for most of the foreign and global variables at the 5% significant level.

C3: Impact elasticity of foreign variables on domestic variables

Table D2 provides the contemporaneous effect of the foreign (starred) variables on their domestic (bank level) counterparts, which can be interpreted as the impact elasticity of the starred variables on the domestic variables. The information presented in this table is particularly informative in describing the linkages across the banks under scrutiny. Most of these elasticities are significant and high in magnitude. In particular, we observe that the elasticity of bank risk captured through nonperforming loans (br_{it} and br^*_{it}) is found to be significant in more than 60% of the sample, mainly for larger banks in the sample. This suggests the presence of relatively strong co-movements across banks' nonperforming loans. Using Bank2 as an example, we see that a 1% increase in nonperforming loans of foreign banks, (br^*_{2t}), will lead to a 2.7% increase in nonperforming loans of Bank2 (br_{2t}). This finding, can be considered as *prima facie* evidence of spillover effects across banks in our sample. Table D2 also shows that for a considerable fraction of banks there is high elasticity of bank return on assets (q_{it} and q^*_{it}) implying strong co-movements between bank specific and foreign return on assets. Separately, when we examine total loan to assets ratio, we observe a mild and negative elasticity (tl_{it} and tl^*_{it}), which are significant only for a few banks.

C4: Average pair-wise cross-sectional correlations

One of the key assumptions of GVAR modeling is that idiosyncratic shocks of conditional $VARX^*$ models are cross-sectionally weakly correlated such as $Cov(u_{it,\ell}, \mathbf{x}^*_{it}) \to 0$, with $N \to \infty$, which ensures that foreign bank variables are weakly exogenous. To see whether foreign variables are effective in reducing the cross-sectional correlation of idiosyncratic shocks across all variables in the GVAR, we have computed the average pairwise cross-sectional correlation for the level and the first differences of the endogenous variables in the model and the associated residuals.[10] This approach relates to the cross-sectional dependence test proposed in Pesaran (2004). In particular, conditioning the bank specific models on foreign variables, the remaining correlation across banks is expected to be small.

Table D3 presents the average pair-wise cross sectional correlations for the level and the

[9] Note the specification of marginal model in (7) is independent of the conditional $VARX^*$ model in (1). Therefore, the lagged orders p^*_i and q^*_i are not necessarily the same as the p_i and q_i of bank specific $VARX^*($ $p_i, q_i)$.

[10] In particular, we compute, both in levels and in first differences, the average pair-wise correlation of bank-specific variables. For example, the average pair-wise correlation of the bank risk of bank i is given by: $\overline{br}_i = \frac{1}{N}\sum_{j=1}^{N} \rho_{ij}(br)$ where $\rho_{ij}(br)$ is the correlation of the bank risk of bank i with the bank risk of bank j, N is the number of banks included in our sample. The residuals are obtained after estimating all bank-specific $VARX^*(p_i, q_i)$ models.

first difference of the endogenous variables in the model, as well as the associated model's residuals. Results show that the average cross sectional correlation is generally high for the level of endogenous variables and declines for the first difference and the estimated $VARX^*$ residuals. In particular, the highest cross-sectional correlation is observed for the level of nonperforming loan of large banks. This observation is consistent with the view that nonperforming loans reflect changes in the underlying macroeconomic environment. Whereas the return on assets and loans to assets ratios show a lower correlation.[11] This finding suggests that changes in return on assets and loan to assets ratio reflect changes in bank behaviour concerning managerial and policy preferences.

When the first difference of the variables are considered, the correlations fall for all variables and banks. The cross-sectional correlation for the residuals for all $VARX^*$ models is very small, indicating that the model is successful in capturing the common effects among the variables. Moreover, these results show the importance and usefulness of modeling the bank specific foreign variables, as confirmed by the size of the bank residual correlations.

Appendix D: Tables

Table D1: Test for Weak Exogeneity at the 5% Significance Level

Bank's name	**F test**	**Critical value 5%**	**Nonperf. loans**	**return on assets**	**Loan to assets**	**GDP**	**Interest rate**	**hpi**
Bank2	F(2,76)	3.1170	3.4775	2.7901	1.1392	5.7994	0.0127	0.7164
Bank3	F(1,77)	3.9651	0.0009	5.1588	0.1122	2.1454	0.4877	1.7710
Bank4	F(1,77)	3.9651	1.5094	1.9309	0.8267	0.8158	0.0072	0.3070
Bank5	F(3,75)	2.7266	0.9018	0.1347	0.3269	1.5914	2.0194	0.3593
Bank6	F(1,77)	3.9651	0.0412	0.0553	1.4257	0.0643	0.0640	3.9422
Bank7	F(3,75)	2.7266	0.5578	2.9591	1.4253	1.2630	7.2486	0.4582
Bank11	F(3,75)	2.7266	0.8892	2.1146	2.4606	0.9227	0.3254	0.9293
Bank13	F(3,75)	2.7266	0.4823	4.2033	2.4025	1.6600	3.8017	1.7200
Bank15	F(2,76)	3.1170	2.3757	1.0253	1.5619	2.6316	0.4066	1.5268
Bank16	F(1,77)	3.9651	0.3926	0.7289	0.1981	0.1039	0.8308	0.2694
Bank17	F(1,77)	3.9651	0.1077	1.5679	1.4994	0.6576	0.4908	1.0246
Bank19	F(2,76)	3.1170	0.7606	2.1864	1.0255	0.5495	0.9425	1.2365
Bank21	F(2,76)	3.1170	0.0665	4.6269	2.9454	1.9350	2.4128	1.7943
Bank25	F(2,76)	3.1170	0.4716	0.3736	5.8730	0.4513	0.1984	3.8645
Bank26	F(2,76)	3.1170	1.4335	2.3407	0.9013	0.3357	4.3716	0.2398
Bank29	F(1,77)	3.9651	1.2707	0.2132	1.1634	1.2994	0.4682	0.2249
Bank30	F(2,76)	3.1170	0.1343	0.8612	2.9386	0.3735	3.3881	0.7690
Bank33	F(3,75)	2.7266	1.1061	4.5798	0.4717	1.5142	0.5416	0.2772
Bank36	F(1,77)	3.9651	0.4226	2.0718	0.8569	4.7184	0.9441	1.3861
Bank38	F(3,75)	2.7266	0.7324	0.3926	2.4811	0.9101	7.2336	1.2041
Bank39	F(1,77)	3.9651	0.9952	0.0377	1.6445	0.2445	0.3726	0.0984
Bank42	F(2,76)	3.1170	0.8712	0.1628	1.9042	1.6287	1.2571	0.0213
Bank46	F(1,77)	3.9651	0.0097	1.4337	0.1994	8.5880	0.0048	1.6164
Bank51	F(2,76)	3.1170	1.6700	3.8676	0.6857	0.1578	1.3134	0.1268
Bank53	F(2,76)	3.1170	1.9231	0.2885	0.1015	1.0184	1.9646	0.0007
Bank54	F(3,75)	2.7266	0.1378	4.4748	0.9187	1.4493	1.2937	0.5683
Bank56	F(3,75)	2.7266	0.1013	2.4943	0.4794	0.9546	3.0382	1.0555
Bank58	F(3,75)	2.7266	0.7165	3.5846	0.8237	0.1425	2.1528	1.3477
Bank59	F(2,76)	3.1170	0.3865	0.3588	0.0683	0.0968	4.7613	0.0283
Bank61	F(2,76)	3.1170	1.4397	4.3236	1.7975	2.0857	5.0037	0.1572

Notes: The number which follows the word "Bank" refers to the ranking of the bank among the top 100 banks according to assets values at the end of 2007. This means that Bank2 is the second largest bank in the US in 2007.

[11] Similar results are found by Sgherri and Galesi (2009) who analysed credit growth using data from several countries.

Table D2: Contemporaneous Effect of Foreign Variables on Domestic Variables

	Nonperforming loans	Return on assets	Loan to assets		Nonperforming loans	Return on assets	Loan to assets
Bank2	2.716***	0.886**	0.448	**Bank29**	0.109*	0.001	0.463**
	(11.087)	(3.223)	(1.154)		(1.652)	(0.003)	(3.062)
Bank3	1.374***	0.809***	0.181	**Bank30**	0.03	0.109*	0.068
	(10.035)	(4.535)	(1.268)		(0.485)	(1.569)	(0.452)
Bank4	0.152**	0.227*	0.058	**Bank33**	0.157*	0.011	0.114
	(2.6)	(1.907)	(0.278)		(1.994)	(0.186)	(1.114)
Bank5	0.353***	0.244*	0.145	**Bank36**	0.052	0.064	-0.128
	(4.574)	(1.522)	(1.139)		(0.807)	(0.563)	(-1.031)
Bank6	0.194***	0.064	-0.017	**Bank38**	0.006	0.276**	-0.267**
	(3.832)	(0.714)	(-0.084)		(0.106)	(2.047)	(-2.221)
Bank7	0.056	0.02	0.362**	**Bank39**	0.07*	0.037	-0.236*
	(1.324)	(0.434)	(2.197)		(1.589)	(0.753)	(-1.486)
Bank11	0.178**	0.286**	-0.361	**Bank42**	0.513**	-0.075	0.262
	(2.832)	(2.133)	(-2.06)		(3.195)	(-0.305)	(1.278)
Bank13	0.034	-0.144**	0.236**	**Bank46**	0.005	0.047	-0.053
	(0.782)	(-2.096)	(2.14)		(0.086)	(1.134)	(-0.254)
Bank15	0.605***	0.19**	0.172	**Bank51**	0.02	0.147	0.139
	(9.366)	(1.199)	(0.722)		(0.175)	(1.049)	(0.762)
Bank16	0.129*	0.167*	0.388**	**Bank53**	0.358*	0.171	-0.152
	(1.812)	(1.565)	(2.695)		(1.75)	(1.345)	(-0.838)
Bank17	0.145	0.33**	-0.087	**Bank54**	-0.02	0.34	0.362**
	(1.245)	(2.252)	(-0.401)		(-0.088)	(1.242)	(2.367)
Bank19	0.336**	0.86*	-0.038	**Bank56**	-0.072	0.073	-0.045
	(2.157)	(1.791)	(-0.144)		(-1.395)	(1.279)	(-0.202)
Bank21	0.037	0.509**	0.463***	**Bank58**	0.021	0.055	0.096
	(0.508)	(3.17)	(4.184)		(0.74)	(1.238)	(0.92)
Bank25	0.123**	0.203**	0.701**	**Bank59**	-0.087	0.018	-0.082
	(2.435)	(2.161)	(3.006)		(-0.527)	(0.195)	(-0.577)
Bank26	0.276**	0.263**	0.103	**Bank61**	0.075*	0.017	0.167
	(3.445)	(3.559)	(0.447)		(1.962)	(0.317)	(1.156)

Notes: The table shows the contemporaneous effect of the foreign (starred) variables on their domestic (bank level) counterparts. These effects describe the co-movements among variables across the 30 banks examined in this chapter. * denotes significance at the 10% level ** denotes significance at the 5% level and *** denotes significance at the 1% level. t-statistics are shown in parentheses.

Table D3: Average Pairwise Cross-section Correlations: Variables and Residuals

	Nonperforming loans			Return on Assets			Loan to assets		
	Level	**1st Diff.**	**VECMX***	**Level**	**1st Diff.**	**VECMX***	**Level**	**1st Diff.**	**VECMX***
Bank2	0.6262	0.2070	-0.1004	0.0959	0.0186	-0.0729	-0.1016	0.0556	-0.0193
Bank3	0.6271	0.2351	0.0060	0.2925	0.1304	0.0406	0.0091	0.0766	0.0212
Bank4	0.4342	0.1928	0.0440	0.0732	0.0577	0.0441	0.0215	0.0371	0.0027
Bank5	0.5217	0.1688	-0.0095	0.1682	0.0747	0.0395	-0.1111	0.0020	-0.0022
Bank6	0.3987	0.1030	0.0168	0.2375	0.0791	0.0853	0.1501	0.0364	0.0081
Bank7	0.3773	0.1884	0.0002	-0.1873	0.0289	0.0464	0.1081	0.0570	0.0323
Bank11	0.5037	0.1884	0.0016	0.2276	0.1494	0.0856	0.0700	0.0739	0.0427
Bank13	0.5664	0.1025	-0.0342	-0.0141	0.0299	0.0357	-0.0651	0.0185	-0.0088
Bank15	0.4785	0.1337	0.0166	0.2232	0.1097	0.0107	0.1482	0.0561	0.0093
Bank16	0.3368	0.0868	0.0252	0.0549	0.0257	0.0190	0.1037	0.0438	0.0028
Bank17	0.6446	0.1225	0.0148	0.2945	0.0714	0.0194	-0.0548	-0.0026	-0.0001
Bank19	0.5610	0.0424	-0.0238	0.1025	0.0005	-0.0407	-0.0223	0.0398	0.0712
Bank21	0.5141	0.0823	0.0157	0.2706	0.1307	0.0593	0.1128	0.0582	-0.0107
Bank25	0.3743	0.1545	0.0340	0.1030	-0.0261	0.0192	-0.0348	0.0420	0.0236
Bank26	0.4633	0.0834	-0.0064	0.2031	0.1616	0.0304	-0.0413	0.0250	-0.0242
Bank29	0.5481	0.1825	0.0643	0.1728	0.0570	0.0608	0.1174	0.0688	0.0054
Bank30	0.2182	0.0819	0.0059	0.1416	0.0011	0.0393	0.0220	0.0622	0.0449
Bank33	0.4276	0.1331	0.0009	-0.0063	0.0175	0.0050	0.0274	0.0701	-0.0270
Bank36	0.5142	0.1014	0.0453	0.3146	0.0945	0.0274	0.0820	0.0196	0.0050
Bank38	0.5652	0.1466	0.0217	0.2428	0.1174	0.0488	0.0317	-0.0129	0.0215
Bank39	0.3760	0.1228	0.0336	0.3304	0.0833	0.0214	-0.0397	0.0128	0.0446
Bank42	0.5055	0.0941	0.0071	0.2909	0.0724	0.0047	-0.0368	0.0391	0.0208
Bank46	0.0977	0.0302	0.0153	0.1155	0.0339	0.0438	-0.0118	0.0048	0.0162
Bank51	0.4464	0.0343	-0.0315	0.2710	0.1142	0.0427	-0.0339	0.0441	0.0256
Bank53	0.4130	0.1784	-0.0153	0.1616	0.0626	0.0215	0.1733	0.0300	-0.0095
Bank54	0.3853	-0.0036	-0.0150	0.2367	0.0830	-0.0051	-0.0610	0.0770	0.0615
Bank56	0.2955	0.0510	0.0168	0.2447	0.0546	0.0178	0.1248	0.0396	0.0243
Bank58	0.3619	0.0223	-0.0087	0.1919	0.0114	0.0159	0.0717	-0.0031	0.0066
Bank59	0.5834	0.0209	0.0161	0.2528	-0.0494	-0.0422	0.1040	0.0915	0.0250
Bank61	0.4052	0.1383	-0.0178	-0.0678	0.0425	0.0783	0.1724	0.1068	0.0398