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

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Abstract

Employing data from thirty large banks in the US, 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 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. The results are confirmed for banks' Z-score.

Keywords: Risk-taking channel, GVAR, monetary policy shocks, spilloverover effects.
Jel Classification: E44; E52; G01; G19; G29.

1 Introduction

Long before (two years) 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.

In response to these events, researchers have begun to examine the link between monetary policy and financial institutions' appetite for risk. Based on the underpinnings of the theoretical research on the risk-taking channel (e.g. see Borio and Zhu, 2012), a number of researchers have 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, have shown that lower overnight rates induce banks to lend more

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[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 in response to developments in credit and asset markets.

to borrowers with bad credit history who have a higher per-period probability of default. Examining bank level data from Bolivia, the US and the EU, similar observations were reported by researchers including Ioannidou et al. (2015), Altunbas et al. (2010) and Delis and Kouretas (2011). Several other researchers, using VAR or FAVAR methodologies, have also shown that expansionary monetary policies induce banks to engage in more risky activities (e.g. Buch et al., 2014 and Angeloni et al., 2015).

In this study, we contribute to the literature on risk-taking channel by implementing the Global Vector Autoregression (GVAR) methodology. We also examine the heterogeneity of banks' risk-taking behaviour in response to monetary policy shocks and whether shocks are transmitted across banks (spillover effects) with differing characteristics. In this context, the GVAR methodology (see Pesaran et al., 2004) is most suitable as it solves the dimensionality problem by decomposing the underlying large VARs into smaller conditional models that are linked together by cross-sectional averages while no restrictions are imposed on the dynamics of the individual sub-models. As the model provides a flexible means to compute the interlinkages between the variables of interest in comparison to its alternatives, we can address issues that have not been examined in the previous literature such as the spillover effects or heterogeneity of bank responses to monetary policy shocks.[2]

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 will be related to future economic conditions suggests for the presence of an indirect association between

[2]Alternatives to GVAR modeling approach are the FAVAR model or the panel VAR (PVAR). Both FAVAR and PVAR can be viewed as a data shrinkage processes. However, while in the former model 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.[3,4] Therefore, in investigating the effects of monetary policy on banks' risk taking attitude, one should account for the presence of endogeneity between variables, as these variables would respond simultaneously to expected macroeconomic conditions.[5]

To overcome this problem in an empirical investigation, a monetary policy shock that is orthogonal to expected loan defaults should be used. To that end, it is possible to 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.[6] In contrast, we modify the RR approach such that the parameters of their model are allowed to be time-variant with regime switching.[7] We follow this route because the RR approach imposes the restriction that the role of forward-looking variables in the central banks' reaction function remains constant across time. Our modification is most meaningful given the findings of Barakchian and Crowe (2013) who argue that not only Fed has become more forward-looking after 1988 but also a RR based monetary policy shock 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 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 long-run, the magnitude and the duration of banks' reaction to the shock varies. In relation to these observations, it turns out that banks' heterogeneous risk-taking responses to monetary policy shocks relate to their capital structure. Furthermore, when we examine the impulse response functions, we provide evidence that bank size plays an important role in the transmission of shocks

[3] Bernanke and Gertler (2000) argue that the central bank should react to asset prices only if the latter undermines inflation stability.

[4] The minutes of the FOMC did not discuss issues of financial stability before the crisis of 2007. See for instance the speech by the former chairman of Federal Reserve Bernanke (2008).

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

[6] Including information on central banks' forecast on expected defaults would be useful to construct this measure. Unfortunately, such information is not available.

[7] 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.

(spillover effects): an adverse shock to 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 a smaller bank. We confirm our findings using banks' Z-score as an alternative measure for bank risk. The analysis uses quarterly data and covers the period 1985Q1 to 2007Q4 during which agency problems between borrowers and lenders were low, as it is important to examine the presence of a risk-taking channel of monetary policy in normal conditions to capture the true relation.

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 interest rates leads to an increase in collateral and asset values of borrowers, which in turn influences banks' risk perceptions or risk tolerance and leads to increases in banks' lending. Banks lend more because they are willing to take on more risk, implying that lending is driven by the behaviour of banks rather than the improvement in the debtors' collateral and repayment capacity.[8] Similarly, Adrian and Shin (2010) argue that monetary easing will boost the value of assets and bank's equity inducing banks to increase their demand for assets. Higher demand for assets will further increase the initial positive impact on asset values paving the way for a more fragile financial system which is exposed to negative shocks to asset prices.

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.[9] Thirdly, transparency of the central banks may enhance the perception that the central bank actions would cut off large

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

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

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. To that end, Dell'Ariccia et al. (2013) provided an analytical model which 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 policy rate has a negative association with bank risk taking behaviour and that it relates to banks' capitalization.

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 loan applications 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 between 1999 and 2003. 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.[10] 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. (2010) who examined a sample of banks in Europe and the US and by Delis and Kouretas (2011) who examined banks in EMU countries.

Several other researchers, using variants of the vector autoregressive (VAR) framework, have shown that the impact of monetary expansion on bank risk might be different across the banking system, time and bank groups. For instance, Angeloni et al. (2015) within a VAR framework investigated the linkages between financial risk, monetary policy and the business cycle in both the US and the Euro area. They argue that monetary expansion increases bank leverage and risk. Buch et al. (2014), using a FAVAR model, which included both macro and bank level data from the Call Reports, have shown that expansionary monetary policy

[10] 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.

could induce banks engagement in more risky activities.

We adopt an approach that differs from the literature by employing a GVAR model to investigate the risk taking behavior of banks as we examine the movements in nonperforming loans in response to an expansionary monetary policy shock. In our investigation, we also discuss whether there is any type of systematic heterogeneity in the way banks react to exogenous shocks and examine the possibility 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 analysis. One 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 overcome the curse of dimensionality, researchers have proposed several alternative approaches. For example, factor models can be interpreted as data shrinkage procedures, which summarise the information of a large data 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.[11] 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 a component that is common across cross-sectional units, across all variables, a variable specific component, lag specific component and idiosyncratic effects.

Unlike the panel VAR, the GVAR approach solves the dimensionality problem by breaking down the underlying VAR model into a small number of conditional models which are linked together via cross-sectional averages. That is the GVAR methodology imposes an intuitive restriction on cross-sectional linkages without imposing any restriction on the dynamics of

[11] 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 further details see Pesaran (2015)).

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.

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 $\mathbf{x}^*_{it}$ =$\Sigma^N_{j=1} w_{ij} x_{jt}$ where $w_{ij} \geq 0$ is a sequence of bank specific weights with $\Sigma^N_{j=i} w_{ij} = 1$ and $w_{ii} = 0$. We construct the associated weights using the bilateral interbank exposure of banks as we aggregate each bank's interbank assets and liabilities. In particular, we assume that banks spread their borrowing and lending 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, these exposures reflect the relative importance of each 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. This type of programming can be solved by using a matrix balancing algorithm known as the RAS algorithm.[12]

The bank specific VARX$^*(p_i, q_i)$ can be written as:[13]

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

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 $E(u_{it}u'_{jt}) = 0$ 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

[12] The approach discussed here has been used by Upper and Worms (2004), Wells (2002) and Wells (2004). See Appendix A1 for details.

[13] 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).

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:

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

where

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

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 $\mathbf{A}_{i0} = (\mathbf{I}_{k_i}, -\boldsymbol{\Lambda}_{i0})$, $\mathbf{A}_{il} = (\Phi_{il}, \boldsymbol{\Lambda}_{il})$ for $l = 1, 2, ...p$, $\Phi_{il} = 0$ for $l > p_i$ and $\boldsymbol{\Lambda}_{il} = 0$ for $l > q_i$. Estimation of (3) is the first step of the GVAR approach. The second step of the GVAR approach consists of stacking N bank specific models in one large global VAR. In particular, let $\mathbf{x}_t = [\mathbf{x}'_{1t}, \mathbf{x}'_{2t}, ...\mathbf{x}'_{Nt}]'$ 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 $k \times k_i$ dimensional selection matrix so that $\mathbf{x}_{it} = \mathbf{E}'_i\ \mathbf{x}_t = [\mathbf{x}'_{1t}, \mathbf{x}'_{2t}, ...\mathbf{x}'_{Nt}]'$ and $\widetilde{\mathbf{W}}_i$ is $k \times k_i^*$ such as $\mathbf{x}_{it}^* = \widetilde{\mathbf{W}}'_i\mathbf{x}_t$, we have[14]:

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

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

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

[14] 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) is 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 use data only up to 2007 because agency problems between the borrowers and lenders would be larger in crisis periods in comparison to 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 a risk-taking channel of monetary policy in normal conditions to capture the true relation.

Our GVAR framework utilizes several bank level variables extracted from the Call Reports, available on the Federal Reserve Bank of Chicago website.[15] Using this dataset, we construct banks' total loans to assets ratio, (tl_{it}), (rcfd1400/rcfd2170), where the numerator measures total loans and lease financing receivables net of unearned income, and the denominator is total assets. We use return on assets, (q_{it}) as a performance measure, which we calculate as (riad4340/rcfd2170). We also use the share of nonperforming loans to total loans as our main proxy for bank risk (br_{it}).

We also use macroeconomic variables comprised of the log of GDP (y_t), real house prices

[15] All insured banks in the US are required to submit income-statement and balance-sheet data to the Federal Reserve each quarter.

(hp^r_t) and inflation. 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 GDP deflator were obtained from Federal Reserve Bank of St. Louis.

4.1 Constructing the bank level data

To carry out the investigation, we extract bank level data from the largest 100 banks in the US banking system based on banks' 2007 asset value. The analysis focuses on those banks which fully contribute to the dataset for the entire period under scrutiny. We also remove from the dataset those banks whose loan to assets ratio was greater than 1.[16] Furthermore, we eliminated those banks whose nonperforming loans to total loans ratio or return to asset ratio were in the bottom or top percentile at any point in time.[17]

Given the screening, our investigation focuses on 30 banks which commanded 46% of the total assets in the US banking system in 2007.[18] 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 further 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. This means that our sample is quite heterogeneous as visualized by Figure 3, which shows the composition of loan portfolio of each bank. In fact, the theoretical literature on risk-taking channel argues that individual bank characteristics would play a role on the response of risk variables to monetary as well as other shocks. For instance, Dell'Ariccia et al. (2013) have provided an analytical model to show that there is a negative association between banks' risk taking behaviour and monetary policy shocks for well capitalized banks, while no such relation is observed for less capitalized banks.

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. Instead, similar to Buch et al. (2014), we use the share of nonperforming loans to total loans as our main proxy for bank's risk (br_{it}).

[16]28 banks were not present over the entirety of our sample while three banks were found to have loan to assets ratio greater than 1.

[17]39 banks failed to satisfy both criteria.

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

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 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. Nonperforming loans are defined as assets past due 90 days or more (rcfd1403), plus assets placed in nonaccrual status (rcfd1407).

As an alternative proxy of bank risk, we use banks' Z-score. This measure, too, has been widely used in the literature.[19] The Z-score is calculated using the ratio of banks' return on assets and its standard deviation, as well as the equity to assets ratio. 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. Therefore, it is inversely related to the probability of insolvency: the higher the Z-score is, the more stable the bank is. The Z-score is calculated as follows:

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

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 presented in these figures is different, it is worth noting 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 the Central Bank, they might be considered indirectly because expected economic conditions would have a direct impact on future defaults. For example, Bernanke

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

and Gertler (2000) argue that policy 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.

One standard approach that researchers have employed in the literature to identify a monetary policy shock has been the VAR methodology. However, this methodology can be criticized in two aspects. 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.[20] Furthermore, the identification problem gets worse if there is evidence of non-fundamentalness.[21] Second, Benati and Surico (2009) argue that there is a fundamental disconnection 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.[22]

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.[23] However, the RR approach assumes that the impact of forward looking variables on the central bank's reaction function remain 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

[20] 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.

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

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

[23] 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.

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.[24]

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 do 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 unrelated to fundamentals. 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.[25] 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 Fed's reaction function.[26]

5 Empirical analysis

In this section we present and discuss our empirical results. As a prerequisite, we start our investigation by testing the order of integration of the endogenous and exogenous variables. We then examine the endogeity of bank specific foreign variables ($\mathbf{x}_{it}^{*}$). Next, we discuss findings from 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 specific banks. In particular, we present details on spillover effects arising from a shock from the largest and the smallest banks. Lastly, we confirm our findings using banks' Z-score, as an alternative measure of bank risk.

[24]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.

[25]Davig and Leeper (2007) argue that ongoing regimes changes create expectation formation effects that can change 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.

[26]See Appendix A2, which lays out our extension to the RR approach.

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

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

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 and $br_{it}^*, q_{it}^*, tl_{it}^*$ and rr_t, respectively. Note that by construction, monetary policy shocks (rr_t) are assumed to be exogenous. Hence, it is included in the vector of exogenous variables. 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.

5.1 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).[27] The unit-root test results suggest that we cannot reject the hypothesis of a unit root for most of the variables.[28] We also find that the global variables and output are both integrated of order one. Results are given in Appendix B, Tables 4 and 5, respectively.

5.2 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 group-specific domestic variables ($\mathbf{x}_{it}$) to the group-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 disequilibrium errors do not have any information about the marginal distribution of $\mathbf{x}_{it}^*$.

[27]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).

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

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:

$$\Delta x_{it,\ell}^* = c_{i0,\ell} + \sum_{j=1}^{r_i} \delta_{ij,\ell} ECM_{i,t-1}^j \sum_{s=1}^{p_i^*} + \phi_{is,\ell} \Delta \mathbf{x}_{it-s} + \sum_{s=1}^{q_i^*} \theta_{is,\ell} \Delta \mathbf{x}_{it-s}^* + \sum_{j=0}^{j=1} \psi_{ij,\ell} \Delta \mathbf{d}_{t-j} + u_{it,\ell} \tag{8}$$

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 (8) p_i^* and q_i^* are the orders of lagged changes of domestic and foreign variables; $(\mathbf{x}_{it})$ and $(\mathbf{x}_{it}^*)$, respectively.[29] 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 (8). The F-test results, which we summarize in Table 6, Appendix B, show that the weak exogeneity assumption is not rejected for most of the foreign and global variables at the 5% significant level.

5.3 Impact elasticity of foreign variables on domestic variables

Table 2 provides the contemporaneous effect of the foreign (starred) variables on their domestic (state level) counterparts, which can be interpreted as the impact elasticity of the starred variables on the domestic variables. 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 large banks. This suggests the presence of relatively strong co-movements across banks' nonperforming loans. Using Bank 2 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 2 also shows that for a considerable fraction of banks there is high elasticity of bank return on assets (q_{it} and q_{it}^*)

[29]Note the specification of marginal model in (8) 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, $q_i)$.

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.

5.3.1 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.[30] 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 3 presents the average pair-wise cross sectional correlations for the level and the 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.[31] 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

[30] 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.

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

the variables. Moreover, these results show the importance and usefulness of modeling the group specific foreign variables, as confirmed by the size of the bank residual correlations.

6 Impulse response function analysis

In what follows, we present the time profile of the impact of shocks to exogenous variables and the spillover effects. In particular, 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. We also provide evidence that our findings are confirmed when we use banks' Z-score as an alternative proxy for risk taking behaviour.

6.1 Impulse Response to a 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 the risk variables are more sensitive to downward moments (see Lopez et al., 2011). In what follows, we examine the behavior of banks' nonperforming loans and confirm our observations through the movements in banks' Z-score in response to an expansionary monetary policy shock.

Response of nonperforming loans

Figure 6 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, we see that 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 bank risk channel (see, for example, Altunbas et al., 2011 and Delis et al., 2017).

The dynamics of nonperforming loans can be explained as follows. As the collateral and asset values of potential borrowers increase following an expansionary monetary policy shock, banks extend credit to credit worthy as well as risky borrowers. 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, it is expected that a fair number of riskier borrowers would fail to comply with their commitments rendering an increase in nonperforming loans. In fact this is what we observe in Figure 6.

It should be noted that the reaction of nonperforming loans to the monetary policy shock varies across banks. The heterogeneity of bank response to a monetary policy shock is consistent with the theoretical predictions. To that end, Dell'Ariccia et al. (2013) 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 would exhibit low risk (for instance Bank2, Bank13, Bank26, Bank33 and Bank61), whereas, banks with high equity capital ratio (for instance Bank5 and Bank7) would show stronger and longer increase in nonperforming loans. See Figure 7, which visually presents banks' average equity capital ratios.

Response of return on assets

Figure 8 depicts the response of return on assets to an *expansionary* monetary policy shock. There is evidence that return on assets would increase in the short run but fall in the medium horizon. This is consistent with the results observed in Figure 6 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.

It is useful to recall that the initial aim of the policymakers through a negative change of the policy rate is to achieve higher economic growth and lower unemployment by inducing businesses to increase their fixed investment expenditures. However, the bank level data that we examined 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 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 in the literature is whether there is evidence of spillover effects of credit risk within the banking system. To examine the possibility of 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.[32] Results, which are available upon request, do not provide clear evidence of spillover effects. 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 examined the impact 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 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 banks in our sample.

Figures 9 and 10 provide the response of banks to a positive shock to the nonperforming loans of Bank3 and Bank61 (i.e. large and small banks), respectively.[33] Figure 9 shows that the nonperforming loans of banks increase significantly when an adverse shock emanates

[32] Output shock or monetary policy shock can also be considered as a global shock. However, although we identified monetary policy shocks using the narrative approach of Romer and Romer (2004) it is a rather impossible task to identify the effect of other endogenous global shocks in a GVAR (see Pesaran, 2015).

[33] 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.

from Bank3.[34] In contrast, Figure 10 provides evidence that the remaining banks in the system are not affected significantly when the shock emanates from Bank61.

The presence of spillover effects from a large and risky bank to the rest of the banks in the system should be of great concern to the policy makers. Given our findings, there is a firm basis for regulators and policy makers to closely monitor large banks, as these banks have the capacity to lend to riskier borrowers and end up with toxic amounts of nonperforming loans, affecting the rest of the banks in the system, should the interest rates increase unexpectedly. Furthermore, if these banks are also considered to be *too big to fail*, their managers' would not refrain from lending to riskier borrowers in search for higher yield when managers believe that they will be rescued by the Fed. As a consequence, risk taking behaviour of large risky banks could ultimately yield a financial system that is susceptible to crashes.

6.3 Sensitivity analysis

To check the robustness of our findings, we repeated the analysis after replacing nonperforming loans with banks' Z-score as a measure of risk. Overall, the use of this alternative risk proxy provides us with similar findings. In particular, Figure 11 plots the response of Z-score to an *expansionary* monetary policy shock. We find for several banks, (including banks 2, 3, 4, 7 among others), that there is an immediate and significant decline of Z-score following the monetary policy shock. We take the decline in banks' Z-score as an evidence in favour of the risk-taking channel. Interestingly, for four banks the Z-score is found to be increasing, suggesting that bank risk for these institutions reduces when the monetary policy is relaxed. Among these four banks, only Bank13 is relatively large.

When we examine the spillover effects using banks' Z-score as an alternative measure of bank risk, our results remain unchanged. In particular, Figure 12 shows 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 in our system (the Z-score declines). When we inspect Figure 13, which displays the results of the same experiment using Bank61 (the smallest bank) as the source of the shock, we do not observe any significant response from the rest of the banks in the system.

Note that we also investigated the spillover effects from Bank13, whose Z-score increased

[34] 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.

(declining risk) in response to an expansionary monetary policy shock (see Figure 11). We find that an adverse shock to Z-score emanating from this bank does not have any impact on the rest of the banks in our system. This is sensible, as Bank13 has a low risk structure. Overall, this is a useful exercise because it shows that being large is not the real reason why a bank would affect the health of the financial system but its capital structure and riskiness. Results for this experiment are suppressed yet they 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. First, we test for the impact of a downward exogenous change of policy rate on banks' risk taking activities. Second, we discuss heterogeneity of banks' response to exogenous monetary policy shocks. Third, we examine whether there are spillover effects following global and bank specific shocks. These issues are relevant and important to both monetary policy authorities and academic circles as our findings show that central banks can inadvertently destabilize functioning of the financial markets.

Overall, our findings provide further evidence in support for the presence of an active risk-taking channel in the US. In particular, we show that banks' risk taking behaviour in response to a monetary expansion is more pronounced for large, well capitalized banks. This observation is consistent with Dell'Ariccia et al. (2013) who discuss the role of capital structure in relation to banks' risk taking behavior. Finally, we show 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. These results are robust to the use of two alternative bank risk measures; nonperforming loans and the Z-score.

The evidence we present here supports the view that monetary policy affects the risk taking behaviour of financial intermediaries. In particular, we argue that while large banks' managers feel safe due to *too big to fail*, their search for high yield could sow the seeds of the next financial crisis. In this respect, given that standard monetary policy rules ultimately affect the financial markets through several drivers such as credit, liquidity and risk taking, policymakers 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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Table 1: Details of the 30 Banks Used

Name	bankid	rank	location	charter	C.assets	D.assets	pctd.	d.bran	fbran
JPMORGAN CHASE BK NA	852218	2	COLUMBUS, OH	NAT	1,179,390	652,824	55	2852	46
CITIBANK NA	476810	3	LAS VEGAS, NV	NAT	1,019,497	537,861	53	1005	375
WACHOVIA BK NA	484422	4	CHARLOTTE, NC	NAT	518,123	487,894	94	3159	11
WELLS FARGO BK NA	451965	5	SIOUX FALLS, SD	NAT	398,671	398,546	100	4052	2
U S BK NA	504713	6	CINCINNATI, OH	NAT	217,802	216,581	99	2822	1
SUNTRUST BK	675332	7	ATLANTA, GA	SMB	182,628	182,628	100	1942	0
NATIONAL CITY BK	259518	11	CLEVELAND, OH	NAT	134,345	133,894	100	1468	2
STATE STREET B&TC	35301	13	BOSTON, MA	SMB	96,296	82,651	86	2	10
PNC BK NA	817824	15	PITTSBURGH, PA	NAT	90,142	88,357	98	953	0
KEYBANK NA	280110	16	CLEVELAND, OH	NAT	88,081	85,863	97	1158	1
BANK OF NY	541101	17	NEW YORK, NY	SMB	85,952	52,731	61	8	9
CITIBANK SD NA	486752	19	SIOUX FALLS, SD	NAT	79,761	79,761	100	0	0
COMERICA BK	60143	21	DETROIT, MI	SMB	58,543	57,252	98	382	1
FIFTH THIRD BK	723112	25	CINCINNATI, OH	SMB	52,672	52,672	100	415	1
NORTHERN TC	210434	26	CHICAGO, IL	SMB	52,313	33,358	64	17	3
FIFTH THIRD BK	913940	29	GRAND RAPIDS, MI	SMB	48,441	48,441	100	718	0
M&I MARSHALL	983448	30	MILWAUKEE, WI	SMB	48,017	48,017	100	309	0
COMMERCE BK NA	363415	33	PHILADELPHIA, PA	NAT	41,170	41,170	100	343	0
FIRST HORIZON NAT CORP	485559	36	MEMPHIS, TN	NAT	37,608	37,608	100	222	0
HUNTINGTON NB	12311	38	COLUMBUS, OH	NAT	34,914	34,914	100	491	0
COMPASS BK	697633	39	BIRMINGHAM, AL	SMB	34,181	34,181	100	444	0
MELLON BK NA	934329	42	PITTSBURGH, PA	NAT	26,226	22,713	87	26	1
ASSOCIATED BK NA	917742	46	GREEN BAY, WI	NAT	20,532	20,532	100	351	0
ZIONS FIRST NB	276579	51	SALT LAKE CITY, UT	NAT	14,849	14,848	100	169	0
CITY NB	63069	53	BEVERLY HILLS, CA	NAT	14,665	14,665	100	72	0
BANK OF OK NA	339858	54	TULSA, OK	NAT	14,366	13,766	96	79	0
COMMERCE BK NA	601050	56	KANSAS CITY, MO	NAT	13,891	13,891	100	169	0
FIRST-CITIZENS B&TC	491224	58	RALEIGH, NC	SNM	13,327	13,327	100	334	0
FROST NB/CULLEN	682563	59	SAN ANTONIO, TX	NAT	13,307	13,307	100	123	0
VALLEY NB/VALLEY NBC	229801	61	PASSAIC, NJ	NAT	12,364	12,364	100	161	0

Notes: C.assets: Consolidated assets. D.assets: Domestic assets. pctd.: Domestic assets as a percentage of consolidated assets. d.bran: Domestic Branches. fbran: Foreign Branches.

Table 2: Contemporaneous Effect of Foreign Variables on Domestic Variables

	nonper	roa	L/assets		nonper	roa	L/assets
Bank2	2.7153	0.8860	0.4471	**Bank29**	0.1084	0.0002	0.4625
	(11.0865)	(3.2223)	(1.1539)		(1.6519)	(0.0024)	(3.0617)
Bank3	1.3731	0.8089	0.1805	**Bank30**	0.0290	0.1089	0.0678
	(10.0347)	(4.5344)	(1.2676)		(0.4849)	(1.5684)	(0.4512)
Bank4	0.1513	0.2266	0.0579	**Bank33**	0.1568	0.0104	0.1136
	(2.5995)	(1.9063)	(0.2777)		(1.9938)	(0.1854)	(1.1136)
Bank5	0.3523	0.2434	0.1441	**Bank36**	0.0513	0.0640	-0.1275
	(4.5739)	(1.5212)	(1.1382)		(0.8063)	(0.5622)	(-1.0308)
Bank6	0.1932	0.0639	-0.0169	**Bank38**	0.0052	0.2754	-0.2669
	(3.8313)	(0.7136)	(-0.0831)		(0.1058)	(2.0469)	(-2.2204)
Bank7	0.0551	0.0191	0.3614	**Bank39**	0.0694	0.0360	-0.2356
	(1.3231)	(0.4336)	(2.1962)		(1.5882)	(0.7525	(-1.4852)
Bank11	0.1771	0.2854	-0.3604	**Bank42**	0.5122	-0.0743	0.2611
	(2.8315)	(2.1326)	(-2.0590)		(3.1949)	(-0.3046)	(1.2778)
Bank13	0.0332	-0.1431	0.2353	**Bank46**	0.0050	0.0463	-0.0527
	(0.7817)	(-2.0952)	(2.1391)		(0.0855)	(1.1338)	(-0.2535)
Bank15	0.6049	0.1895	0.1712	**Bank51**	0.0193	0.1468	0.1384
	(9.3658)	(1.1988)	(0.7219)		(0.1746)	(1.0484)	(0.7616)
Bank16	0.1281	0.1661	0.3878	**Bank53**	0.3578	0.1710	-0.1516
	(1.8116)	(1.5645)	(2.6942)		(1.7493)	(1.3445)	(-0.8372)
Bank17	0.1449	0.3296	-0.0868	**Bank54**	-0.0197	0.3397	0.3618
	(1.2441)	(2.2514)	(-0.4009)		(-0.0874)	(1.2412)	(2.3665)
Bank19	0.3359	0.8592	-0.0377	**Bank56**	-0.0720	0.0722	-0.0441
	(2.1567)	(1.7901)	(-0.1431)		(-1.3942)	(1.2782)	(-0.2011)
Bank21	0.0360	0.5090	0.4622	**Bank58**	0.0206	0.0547	0.0958
	(0.5075)	(3.1695)	(4.1840)		(0.7394)	(1.2377)	(0.9190)
Bank25	0.1230	0.2022	0.7003	**Bank59**	-0.0864	0.0174	-0.0817
	(2.4341)	(2.1604)	(3.0059)		(-0.5268)	(0.1949)	(-0.5761)
Bank26	0.2754	0.2622	0.1020	**Bank61**	0.0750	0.0168	0.1661
	(3.4442)	(3.5587)	(0.4466)		(1.9614)	(0.3165)	(1.1558)

Notes: t-statistics are given in parenthesis, nonper: Nonperforming loans, roa: Return on assets and L/assets: total loans to assets ratio

Table 3: Average Pairwise Cross-Section Correlations: Variables and Residuals

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

Notes: nonper: Nonperforming loans, roa: Return on assets and L/assets: total loans to assets ratio

Figure 1: Banks' ranking according to assets size

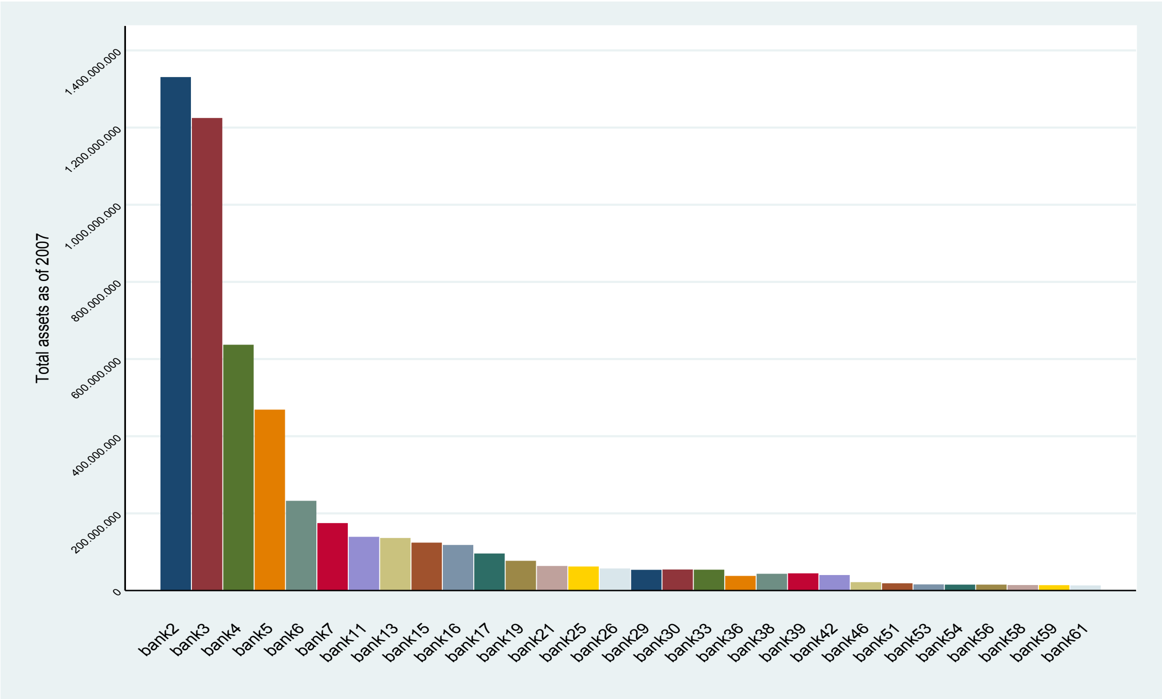


Figure 2: Total Loans

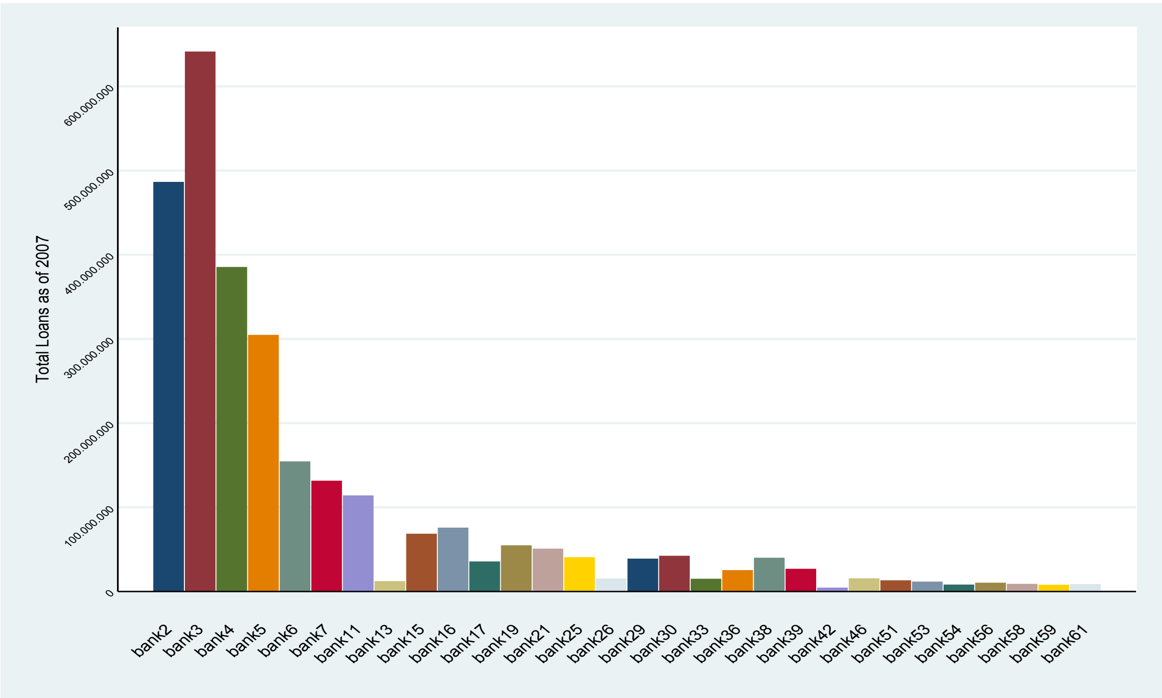


Figure 3: Loan Composition

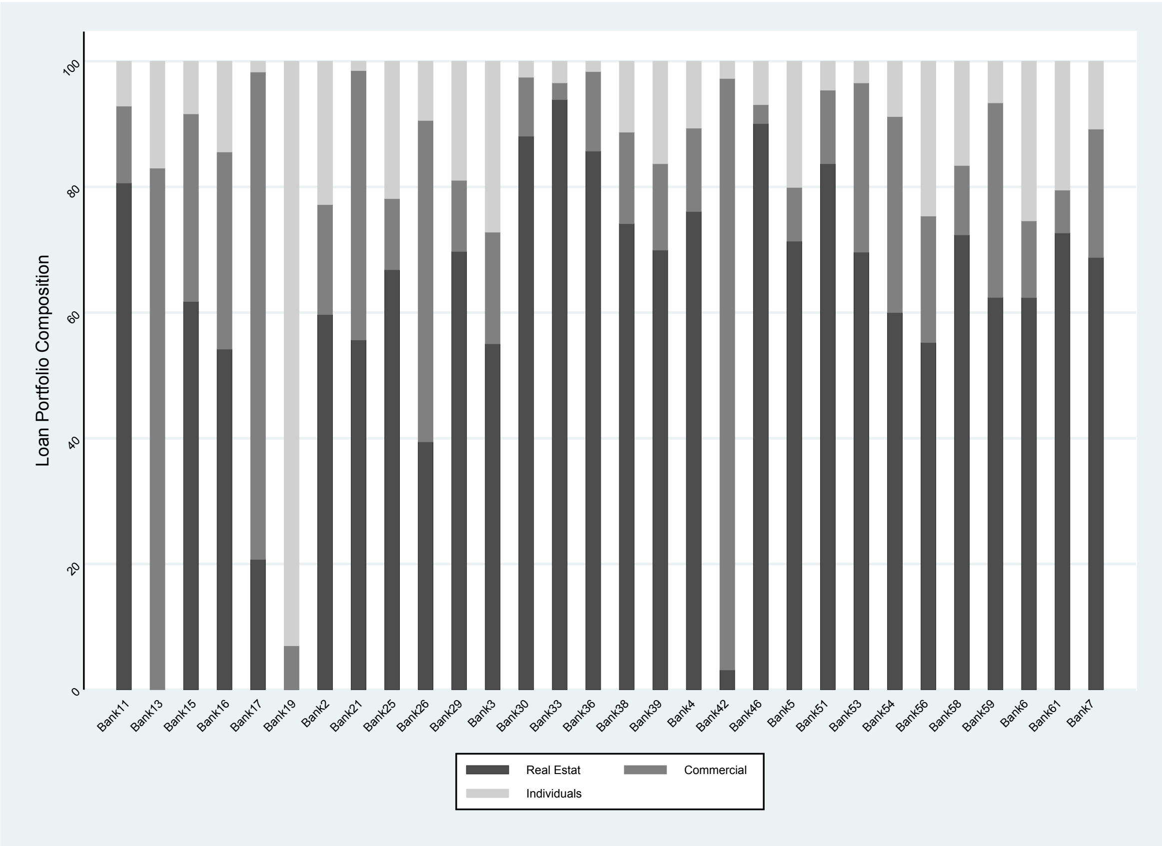


Figure 4: Banks' ranking according to nonperforming ratio

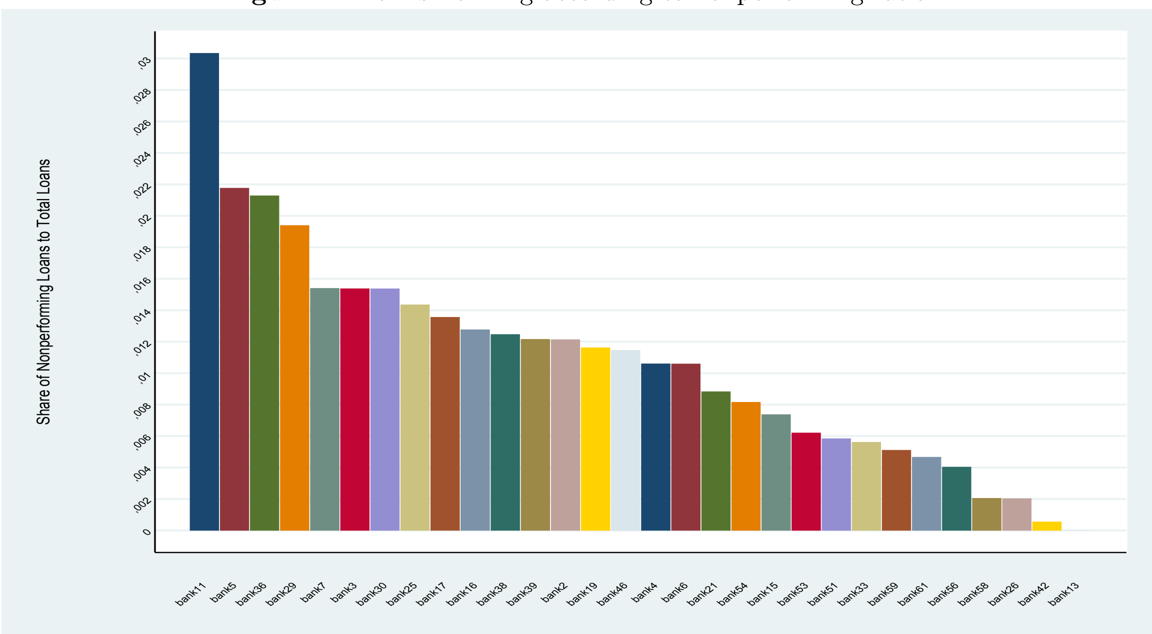


Figure 5: Banks' ranking according to Z-score

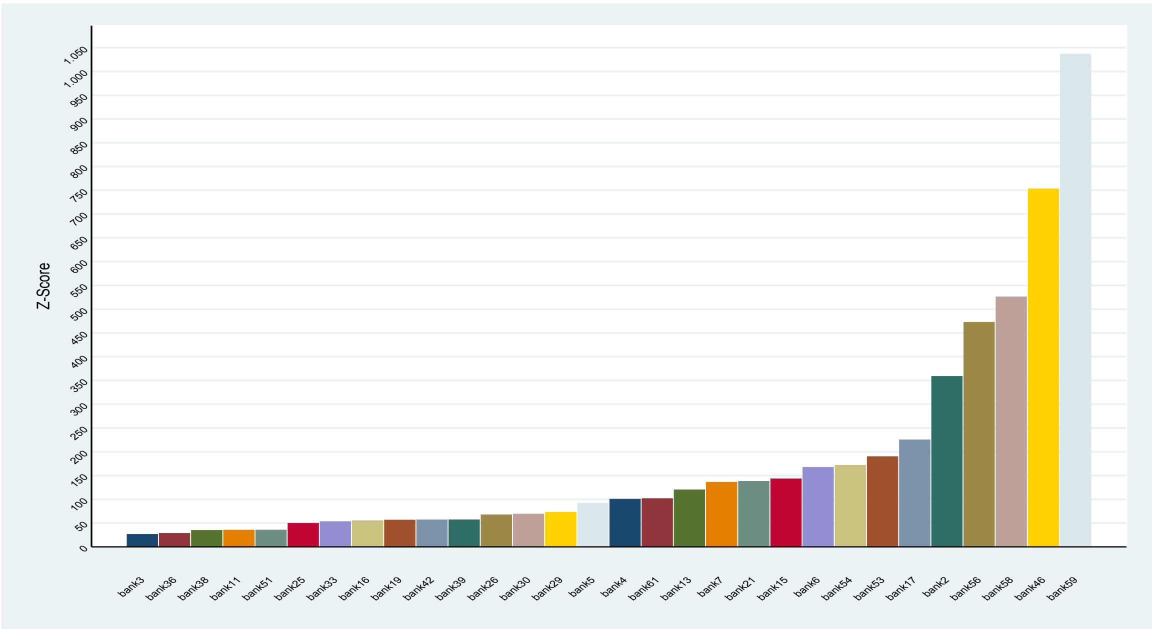


Figure 6: Response of nonperforming Loans To a Negative Shock in Interest Rate

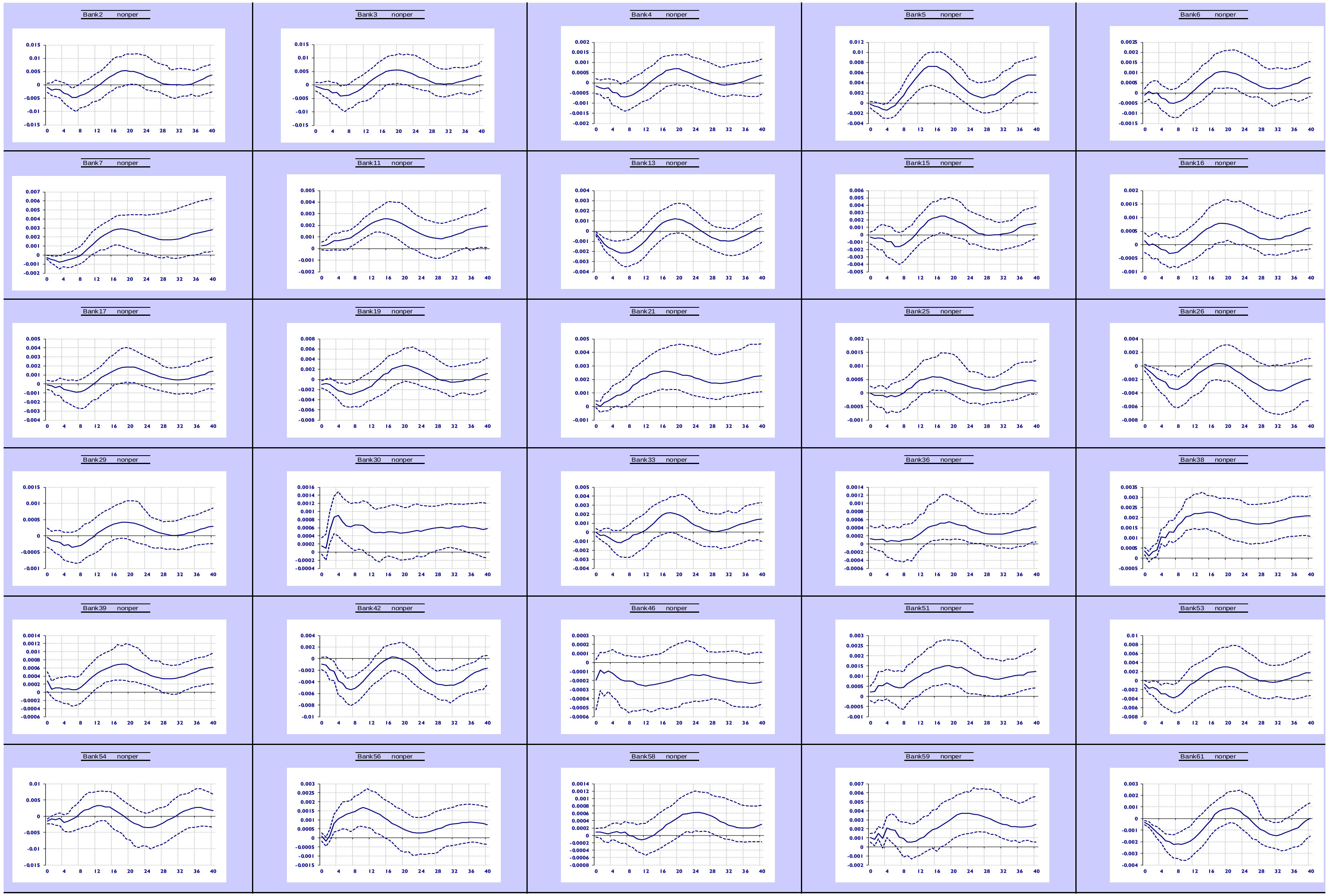


Figure 7: Average Equity Capital Ratio

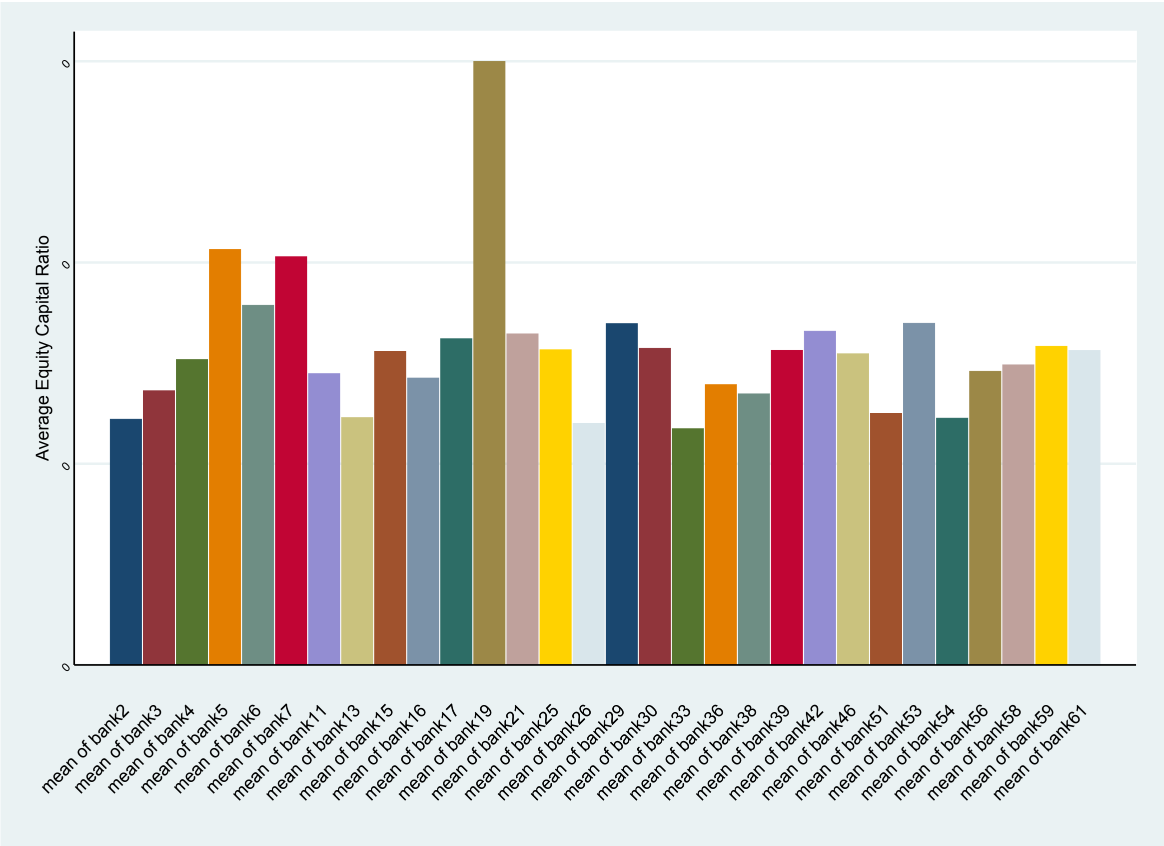


Figure 8: Response of Return on Assets To a Negative Shock in Interest Rate

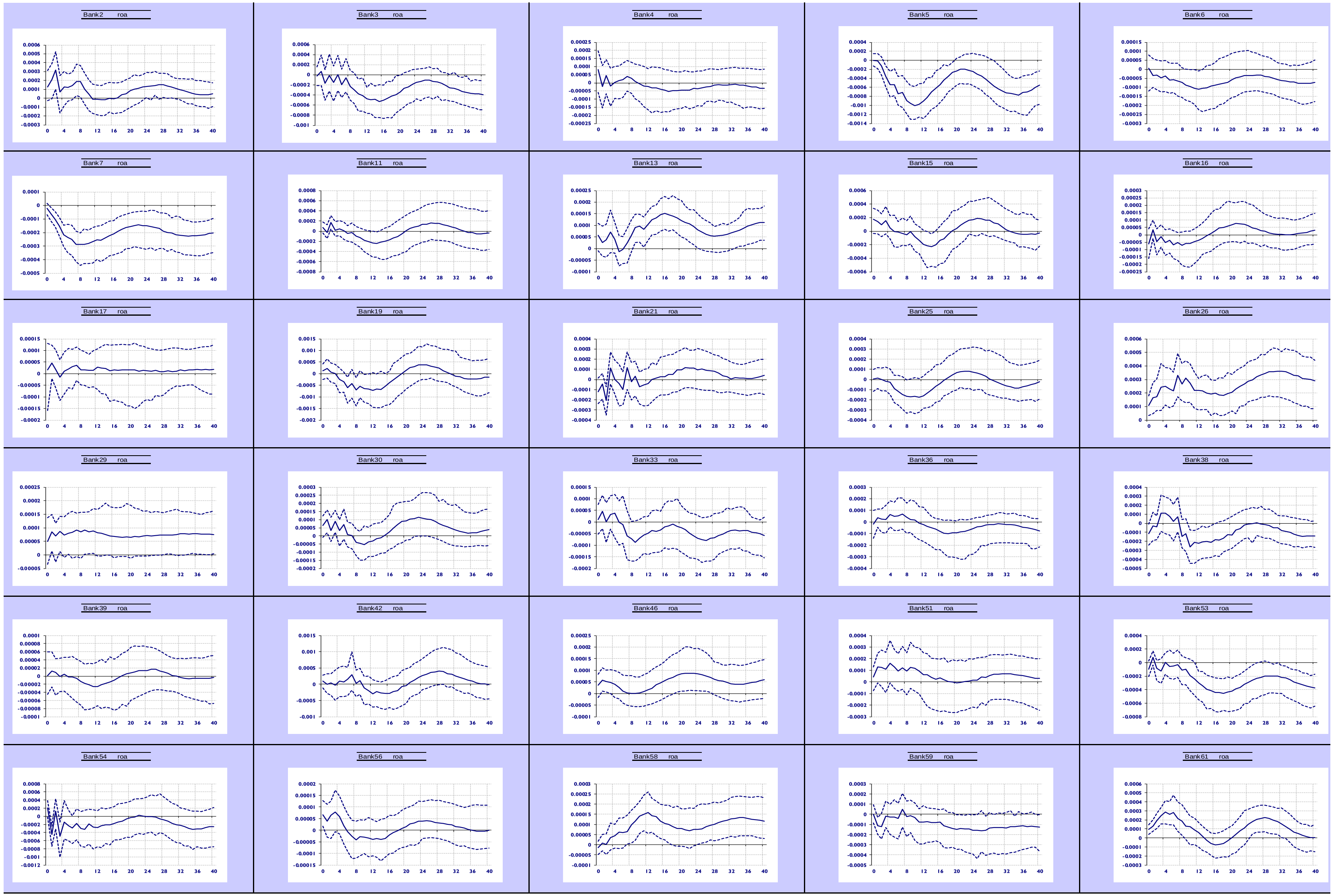


Figure 9: Response of nonperforming Loans To a Negative Shock in Bank3 nonperforming Loans

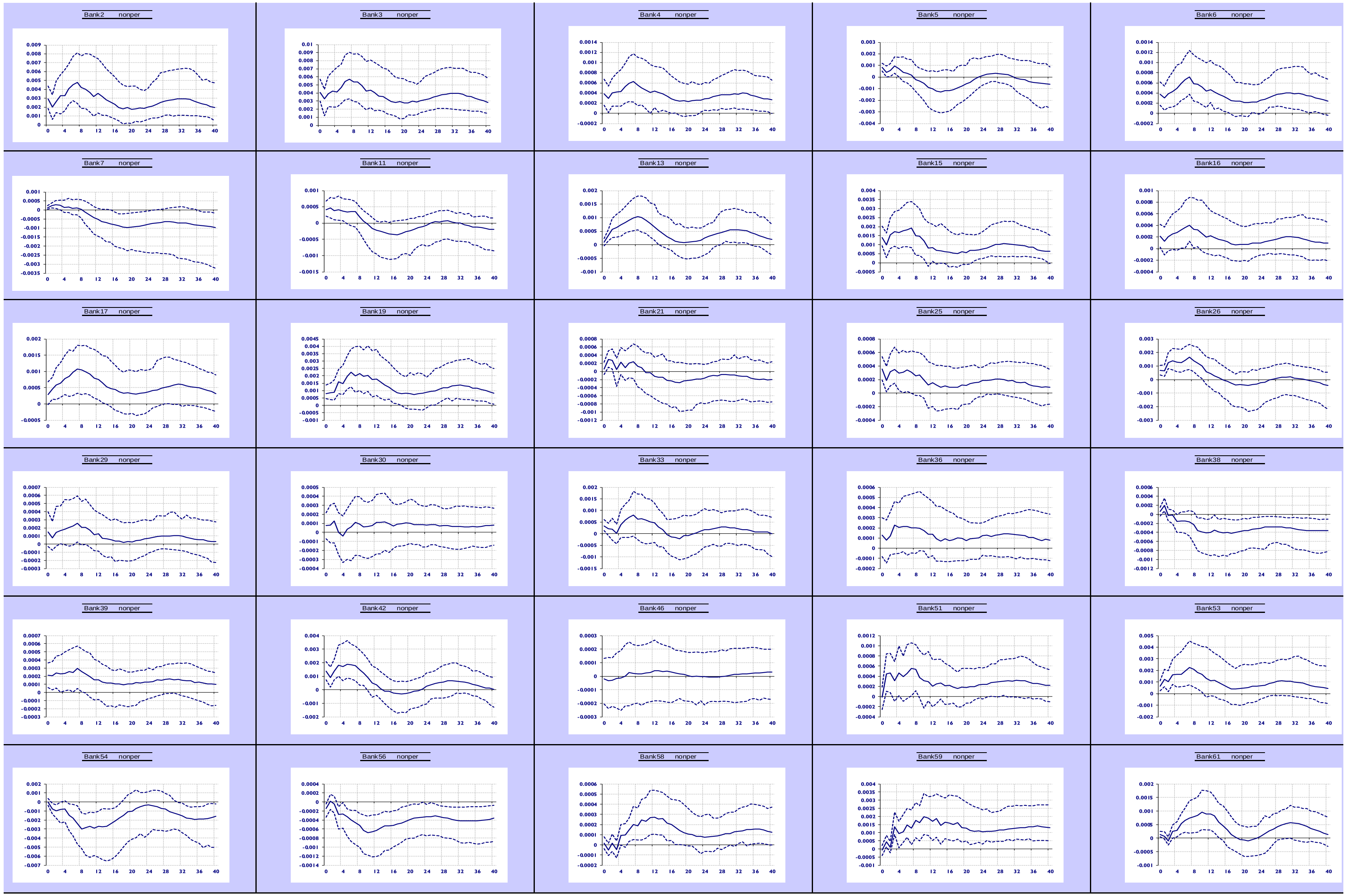


Figure 10: Response of nonperforming Loans To a Negative Shock in Bank61 nonperforming Loans

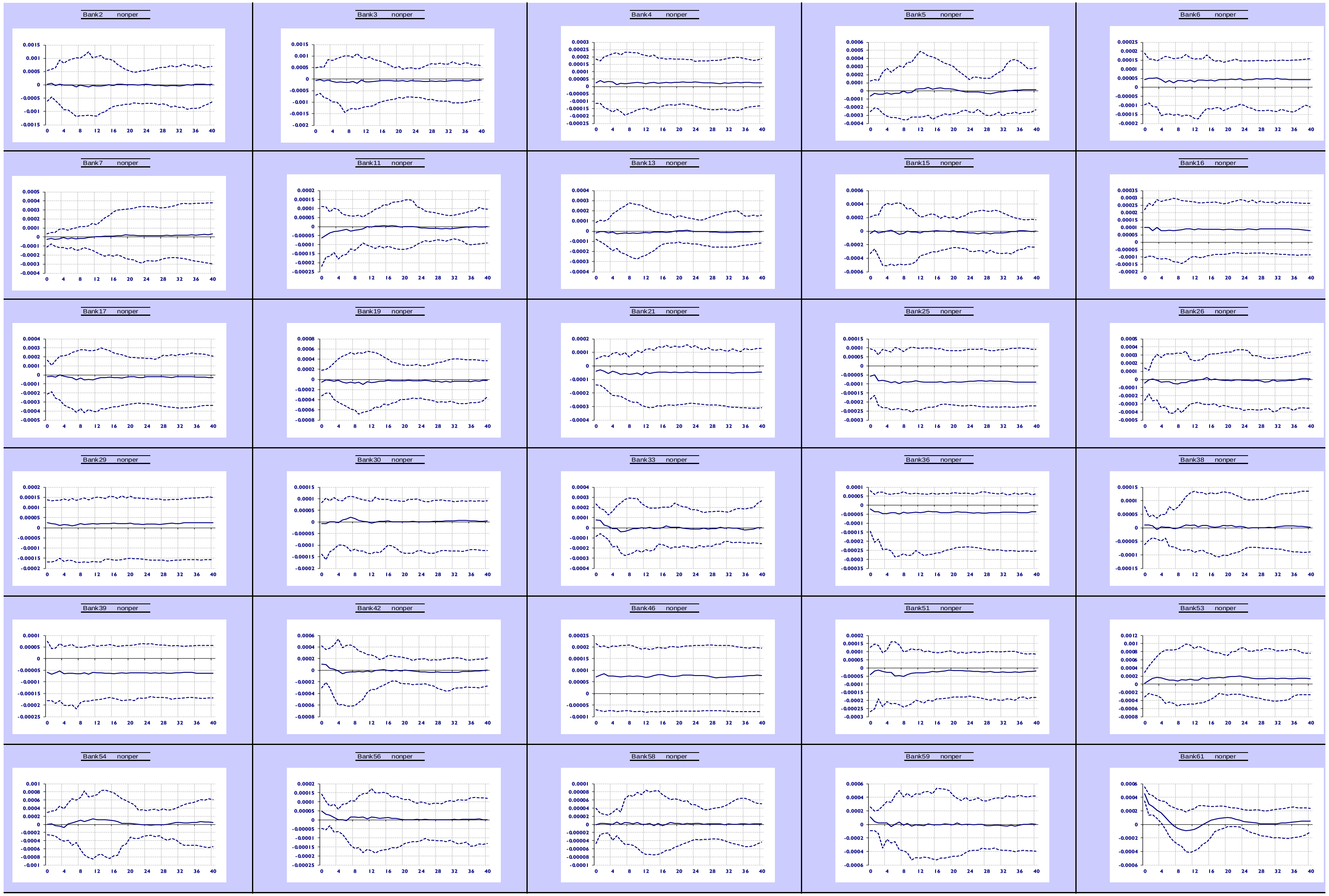


Figure 11: Response of Banks' Z-score To a Negative Shock in Interest Rate

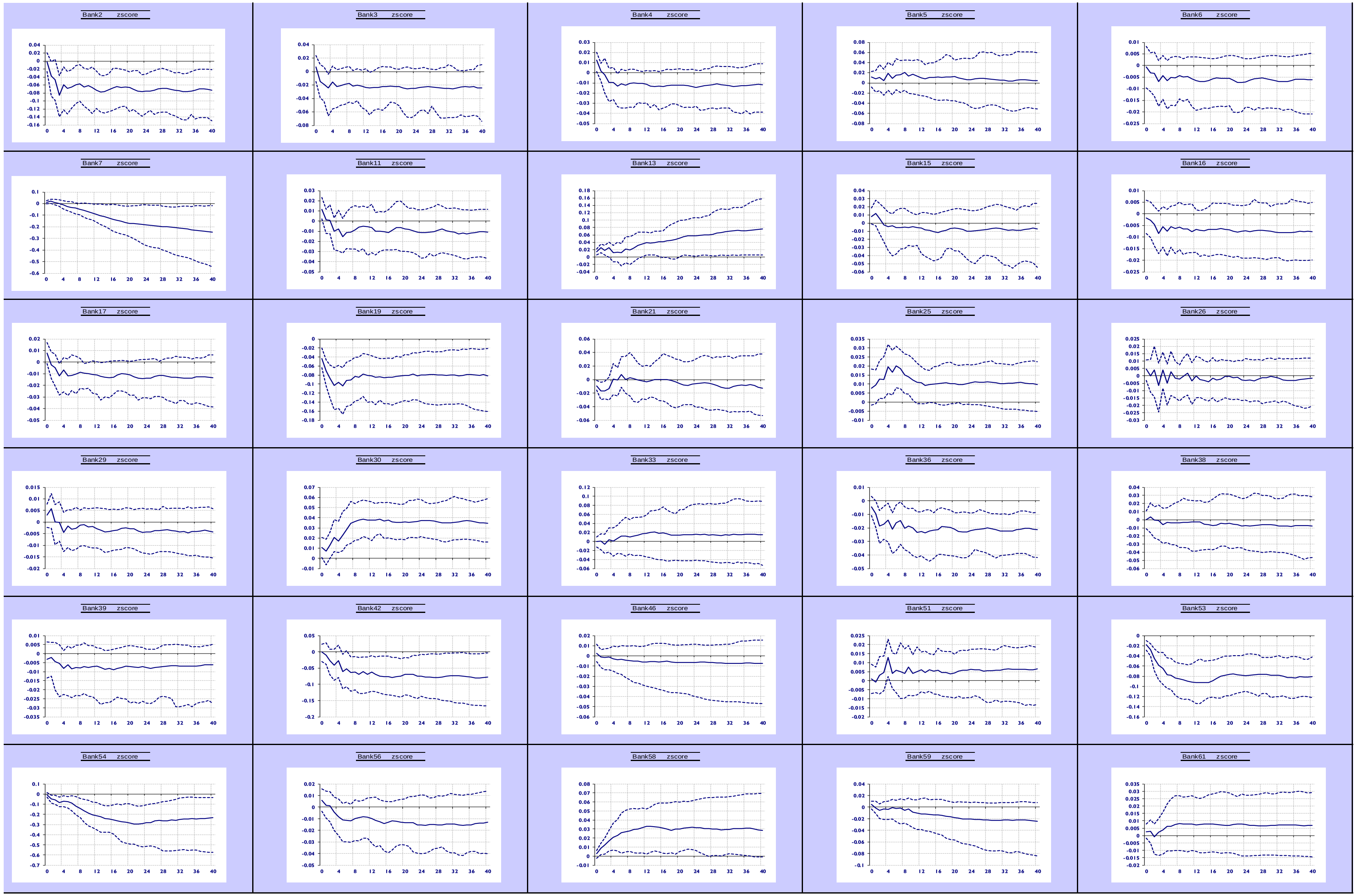


Figure 12: Response of Banks' Z-score To a Negative Shock in Bank3 Z-score

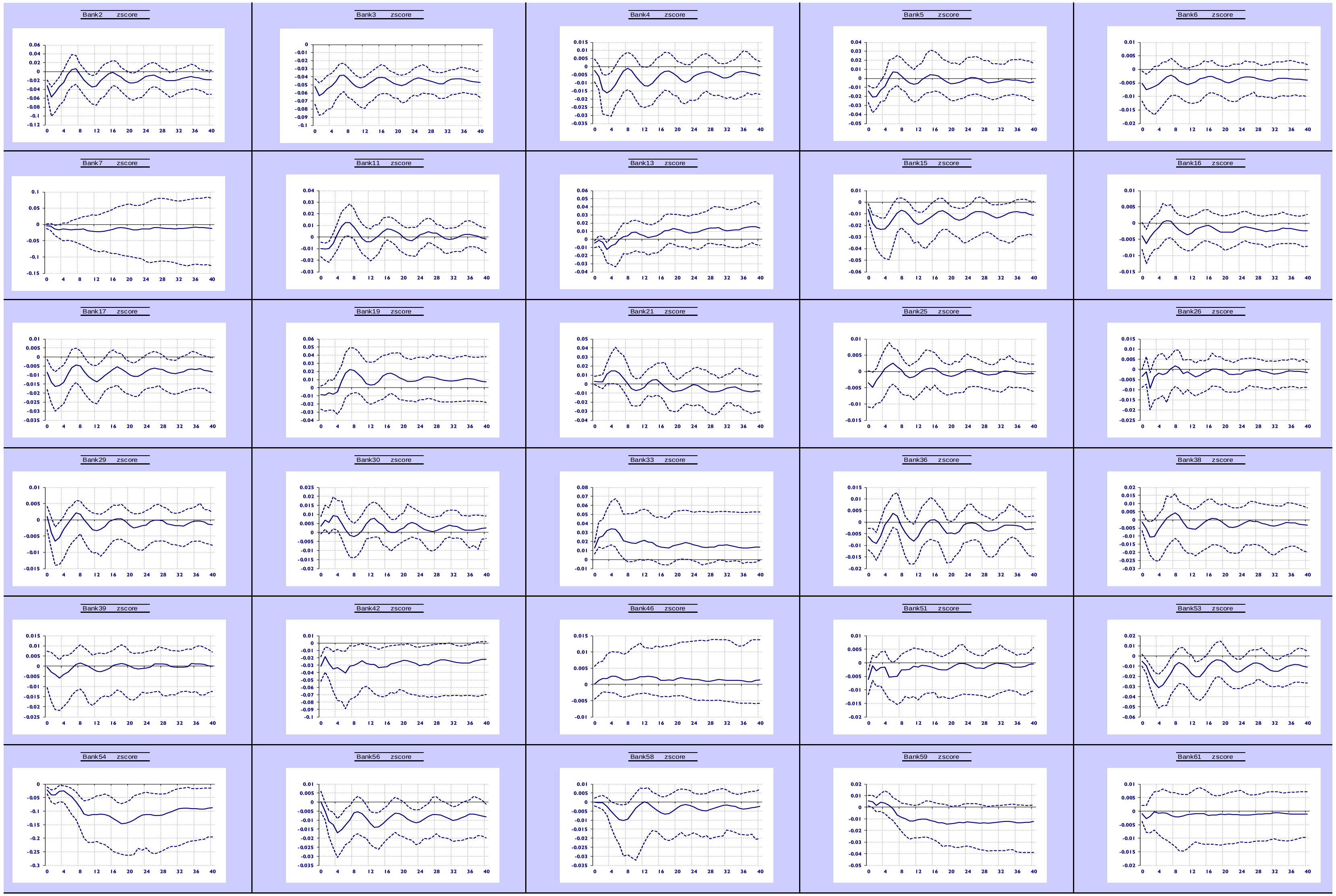
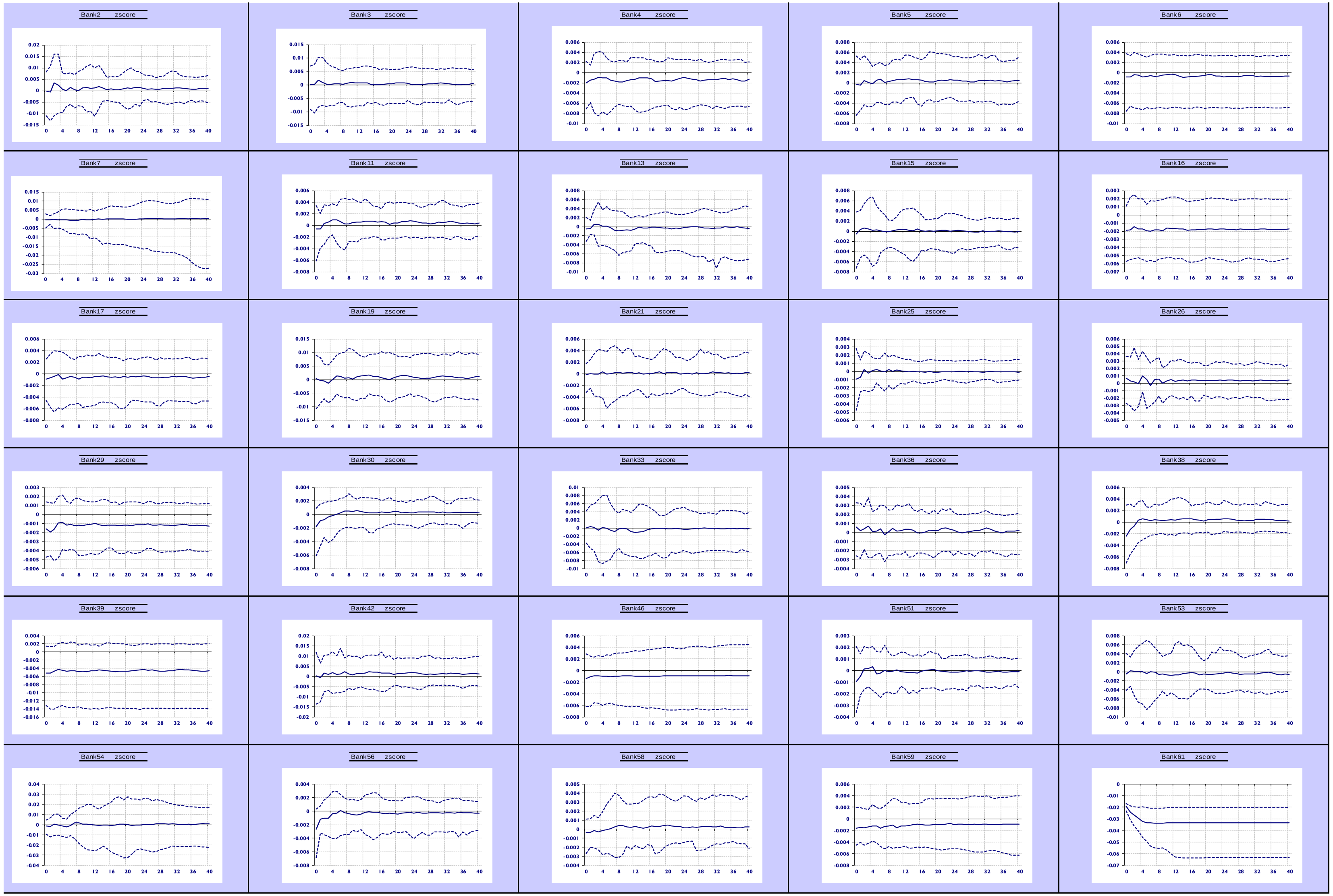


Figure 13: Response of Banks' Z-score To a Negative Shock in Bank61 Z-score



8 Appendix A:

8.1 Appendix A1: Estimating Bilateral Exposure with Incomplete Information

For a system of N banks we are aiming to estimate a matrix of the form:[35]

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

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.[36] 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 $_j = \sum_i x_{i,j}$).[37] 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:

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

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

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

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

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

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

numerically by using RAS algorithm.[38]

8.2 Appendix A2: Romer and Romer (2004) Approach

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

$$\begin{aligned}\Delta ff_m = &\alpha + \beta ffb_m + \Sigma_{i=-1}^{2}\gamma_i\Delta y_{mi} + \Sigma_{i=-1}^{2}\lambda_i(\Delta y_{mi} - \Delta y_{m-1,i}) \\ &+\Sigma_{i=-1}^{2}\varphi_i\pi_{mi} + \Sigma_{i=-1}^{2}\theta_i(\pi_{mi} - \pi_{m-1,i}) + \rho u_{m0} + \varepsilon_m\end{aligned} \tag{9}$$

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 (9) to be time-varying.[39] In particular, we write (9) in a state-space form as follows:

$$y_t = X_t'\xi_t + e_t,\ e_t \sim N(0, \sigma_e^2) \tag{10}$$

$$\xi_t = F\xi_{t-1} + v_t,\ v_t \sim N(0, Q_t) \tag{11}$$

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 (10) and (11) are the measurement and transition equation of (9). 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 (10) consists of filter uncertainty and uncertainty concerning the future shocks:

$$f_{t|t-1} = X_t P_{t|t-1} X_t' + \sigma_e^2 \tag{12}$$

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 Markov process. Therefore, the version of model (10) and (11) with switching effects takes the following form:

$$e_t \sim N(0, \sigma_{e,S_t}^2) \tag{13}$$

$$\sigma_{e,S_t}^2 = \sigma_0^2 + (\sigma_1^2 - \sigma_0^2)S_t,\ \sigma_1^2 > \sigma_0^2 \tag{14}$$

To estimate the model given by equations 10-14, we employ Kim (1994) algorithm.

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

[39] 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.

9 Appendix B: Tables

Table 4:
Unit Root Tests for the Global Variables at the 5% Significance Level

Global Variables	Test	Critical Value	Statistic
gdp (with trend)	ADF	-3.45	-2.423435805
gdp (with trend)	WS	-3.24	-2.627875358
gdp (no trend)	ADF	-2.89	-0.519031945
gdp (no trend)	WS	-2.55	0.749324561
D.gdp	ADF	-2.89	-4.292499674
D.gdp	WS	-2.55	-4.359508673
DD.gdp	ADF	-2.89	-7.201130744
D.gdp	WS	-2.55	-7.481019274
rr (with trend)	ADF	-3.45	-4.75927881
rr (with trend)	WS	-3.24	-4.552806757
rr (no trend)	ADF	-2.89	-4.796044099
rr (no trend)	WS	-2.55	-4.468162659
D.rr	ADF	-2.89	-7.38782521
D.rr	WS	-2.55	-7.056988202
DD.rr	ADF	-2.89	-9.054257724
D.rr	WS	-2.55	-8.90743397
hpi (with trend)	ADF	-3.45	-2.693622333
hpi (with trend)	WS	-3.24	-2.650431281
hpi (no trend)	ADF	-2.89	-1.364924431
hpi (no trend)	WS	-2.55	-1.471405554
D.hpi	ADF	-2.89	-1.610997256
D.hpi	WS	-2.55	-1.892317799
DD.hpi	ADF	-2.89	-10.94849322
Dd.hpi	WS	-2.55	-11.10881054

Notes: rr: monetary policy shock, gdp: output growth, hpi: real house prices index, D: first difference and DD: second difference.

Table 5: Unit Root Tests for the Domestic Variables at the 5% Significance Level

	nonper+Tr	**nonper**	**D.nonper**	**DD.nonper**	**roa+Tr**	**roa**	**D.roa**	**DD.roa**	**L/Asset+Tr**	**L/Asset**	**D.L/Asset**	**DD.L/Asset**
Critical V.	-3.450	-2.890	-2.890	-2.890	-3.450	-2.890	-2.890	-2.890	-3.450	-2.890	-2.890	-2.890
Bank2	-2.046	-0.986	-6.365	-9.506	-3.730	-3.738	-11.115	-7.763	-2.329	-1.176	-6.354	-7.609
Bank3	-2.498	-1.066	-5.221	-6.963	-2.681	-2.052	-4.028	-8.262	-2.595	-1.417	-4.937	-6.568
Bank4	-2.589	-2.566	-4.736	-6.605	-3.412	-3.435	-6.493	-8.884	-1.990	-1.828	-7.538	-8.285
Bank5	-2.669	-2.173	-4.124	-8.845	-3.650	-3.390	-6.050	-8.339	-1.994	-1.637	-5.161	-8.728
Bank6	-2.038	-2.058	-6.431	-7.153	-5.324	-2.490	-6.215	-7.945	-2.544	-2.822	-7.011	-7.075
Bank7	-2.236	-2.328	-3.715	-12.317	-2.792	-1.535	-6.259	-9.114	-2.321	-0.999	-5.911	-7.999
Bank11	-0.498	-0.997	-2.975	-7.964	-1.610	-1.950	-5.360	-7.372	-2.550	-0.526	-6.342	-8.463
Bank13	-2.267	-1.480	-3.850	-11.586	-6.936	-6.937	-9.633	-12.693	-0.815	-1.917	-6.641	-7.327
Bank15	-2.533	-1.327	-6.356	-7.665	-3.799	-3.546	-10.158	-8.749	-1.188	-1.495	-3.706	-10.497
Bank16	-2.594	-2.545	-5.453	-7.217	-1.841	-1.574	-10.549	-8.232	-2.035	-1.192	-5.165	-7.201
Bank17	-1.980	-1.616	-3.748	-10.356	-2.417	-2.202	-7.949	-9.449	-1.254	0.460	-5.106	-8.603
Bank19	-2.632	-1.414	-5.011	-9.142	-3.548	-3.570	-9.618	-8.726	-2.123	-1.066	-6.683	-7.471
Bank21	-2.226	-2.560	-4.130	-13.609	-3.395	-2.061	-7.713	-10.138	-2.320	-1.102	-4.602	-7.843
Bank25	-2.922	-2.998	-4.744	-11.593	-0.235	-0.312	-7.827	-10.435	-2.597	-2.086	-7.150	-8.968
Bank26	-3.462	-2.716	-5.720	-6.912	-2.458	-2.759	-9.361	-11.681	-2.085	0.277	-13.668	-7.754
Bank29	-1.813	-1.962	-4.262	-7.498	-2.841	-2.935	-8.702	-7.206	-2.919	-1.796	-4.231	-14.424
Bank30	-3.263	-3.996	-5.694	-8.351	-2.848	-2.985	-7.018	-9.025	-2.159	-1.215	-5.270	-7.436
Bank33	-2.406	-2.220	-4.842	-8.294	-1.863	-1.341	-7.304	-9.018	-3.003	-1.743	-4.100	-10.754
Bank36	-0.256	-1.406	-5.689	-7.412	-0.002	-1.274	-5.203	-8.084	-2.297	-1.447	-7.657	-8.060
Bank38	-1.884	-2.399	-5.983	-7.477	-3.153	-3.262	-6.562	-8.644	-4.664	-2.014	-7.882	-7.339
Bank39	-2.191	-2.246	-5.536	-7.916	-1.581	-2.229	-7.429	-10.249	-2.673	-2.904	-4.875	-6.398
Bank42	-2.786	-1.271	-6.891	-9.344	-1.820	-1.909	-11.746	-8.591	-1.368	0.175	-5.499	-8.086
Bank46	-3.517	-3.365	-6.917	-7.743	-3.335	-3.550	-9.384	-16.927	-1.922	-2.071	-7.433	-7.197
Bank51	-1.791	-1.284	-7.342	-7.449	-2.352	-2.378	-7.779	-8.528	-1.048	-0.980	-5.319	-8.092
Bank53	-2.048	-1.697	-4.858	-7.336	-1.902	-1.821	-2.848	-8.399	-1.985	-1.588	-6.096	-7.863
Bank54	-2.748	-1.874	-4.645	-6.653	-1.889	-1.141	-8.510	-13.032	-1.874	-2.317	-3.995	-8.831
Bank56	-1.967	-2.546	-6.736	-7.804	-2.405	-1.366	-7.767	-7.927	-1.991	-0.961	-3.693	-10.181
Bank58	-1.699	-1.441	-6.189	-8.360	-3.718	-3.247	-6.241	-7.293	-2.491	-1.969	-5.614	-7.373
Bank59	-1.460	-1.115	-6.614	-8.855	-3.344	-0.840	-10.302	-10.024	-1.942	-0.933	-2.768	-8.711
Bank61	-2.685	-2.466	-3.089	-11.357	-2.454	-1.928	-5.145	-8.435	-2.681	-2.607	-4.085	-7.301

Notes: nonper: Nonperforming loans, roa: Return on assets and L/assets: total loans to assets ratio, Tr: With trend, D: first difference and DD: second difference.

Table 6: Test for Weak Exogeneity at the 5% Significance Level

Country	F test	Fcrit 0.05	nonper	roa	L/Assets	gdp	rr	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: rr: monetary policy shock, gdp: output growth, hpi: real house prices index, nonper: Nonperforming loans, roa: Return on assets and L/assets: total loans to assets ratio.