

Essays in Credit, Banking and Monetary Policy

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Esteban Prieto Fernandez
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1.Gutachter:

2.Gutachter:

Professor Dr. rer. soc. Josef Schmid

Prof. Dr. Claudia M. Buch

Prof. Dr. Wilhelm Kohler

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Introduction

We need to deal better with heterogeneity across agents and the interaction among those heterogeneous agents. [...] (W)e need to better integrate the crucial role played by the financial system into our macroeconomic models. [...] In particular, dealing with the non-linear behavior of the financial system will be important, so as to account for the procyclical build-up of leverage and vulnerabilities.

Jean-Paul Trichet,
Speech at the ECB Central Banking Conference
Frankfurt, 18 November 2010

The 'Great Recession' has put the interaction between the real economy and the financial system at the forefront of both economic research and policymakers. On the one hand the economics profession quickly realized that the workhorse approach to macroeconomic modeling was missing a crucial feature of modern advanced economies: The financial system. On the other hand, policymakers became increasingly aware of the importance of a well functioning financial system and realized quickly that the available models and empirical approaches were of limited help. As Jean Paul Trichet put it at the 2010 ECB Central Banking Conference "As a policy-maker during the crisis, I found the available models of limited help. I would go further: in the face of the crisis, we felt abandoned by conventional tools."

Since then, enormous efforts have been made to overcome the shortcomings for which the models and methods were blamed. The workhorse quantitative models nowadays used in central banks routinely feature some form of financial market imperfections, and attempts are being made to represent the financial system, and its macroeconomic consequences, in a more realistic way. However, a long way is still to go to build models which incorporate the most relevant features of the financial sector for the macroeconomy in a satisfactory manner. Especially issues of heterogeneity in financial markets and the non-linear and asymmetric behavior of the financial system are still under research,

both from a theoretical and empirical point of view. The aim of the present thesis is to contribute to the empirical literature trying to fill these gaps.

The present thesis can be separated into two parts, each consisting of two chapters. The first part, consisting of Chapter 1 and Chapter 2, deals with the behavior of the banking system over the business cycle. Special focus lies in the modeling of the heterogeneity of the banking system and the transmission of macroeconomic shocks *via* the banking system. The second part of the thesis (Chapter 3 and Chapter 4) deals with the asymmetric behavior of the financial system over the business cycle and the time variation in the mutual interaction between the financial sector and the real economy.

The remainder of the introduction gives a more detailed exposition of each chapter.

CHAPTER 1.¹ The exposure of banks to macroeconomic shocks features prominently in recent proposals for regulatory reforms (Basel Committee 2009). Rochet (2004) shows theoretically that banks should face a capital requirement that increases with their exposure to macroeconomic factors. Farhi and Tirole (2012) analyze the incentives of banks to coordinate their exposure to macroeconomic shocks. They argue that banks which react more to macroeconomic shocks should be regulated more tightly. Gersbach and Hahn (2010) propose a regulatory framework under which a banks' required level of equity capital depends on the equity capital of its peers and, in this sense, on the macroeconomic environment. Implementing these proposals however requires information about individual banks' exposures to macroeconomic factors.

With the analysis in this chapter we attempt to inform this debate. Specifically, we provide answers to the following two questions: How are macroeconomic shocks transmitted to individual banks and, in particular, to bank risk? What are the sources of bank heterogeneity, and what explains differences in individual banks' responses to macroeconomic shocks? The analysis in this chapter is based on a factor-augmented vector autoregressive model (FAVAR) as proposed by Bernanke, Boivin, and Elias (2005). Our model extends a standard macroeconomic VAR comprising GDP growth, inflation, house price inflation, and the monetary policy interest rate with a set of factors summarizing conditions in about 1,500 commercial banks. We find that backward-looking risk tends to decline after expansionary macroeconomic shocks while forward-looking bank risk increases after expansionary monetary policy shocks. Furthermore, there is a substantial degree of heterogeneity across banks both in terms of idiosyncratic shocks

¹This chapter is based on the paper "Macroeconomic Factors and Micro-Level Bank Behavior" written jointly with Claudia Buch and Sandra Eickmeier (Buch, Eickmeier, and Prieto forth.b).

and the asymmetric transmission of common shocks. Bank size, capitalization, liquidity, risk, and the exposure to real estate and consumer loans matter for risk and lending responses of individual banks to monetary policy and house price shocks.

Our findings are interesting from a banking regulation perspective. Our results lend support to proposals that higher capital and higher liquidity requirements can enhance the resilience of the banking sector to macroeconomic shocks. Also, smaller banks are more exposed to macroeconomic risk but, at the same time, the systemic impact of these banks on the macroeconomy is rather small. Accordingly, regulatory policy needs to balance different criteria such as the relevance of an institution for systemic risk and its exposure to macroeconomic shocks when deciding upon new capital or liquidity requirements.

CHAPTER 2.² In this chapter we provide an in depth analysis of the 'risk-taking channel of monetary policy'. The risk-taking channel of monetary policy refers to the behavior of banks to engage in *ex ante* riskier projects following expansionary monetary policy shocks. To identify the risk-taking channel of monetary policy we exploit information provided by the *Federal Reserve's Survey of Terms of Business Lending* (STBL). The information available in the STBL allows modeling the behavior of banks' *new* lending, the corresponding interest rates as well as other important loan characteristics for different loan risk categories and different banking groups. Our metric for risk-taking refers to changes in the composition of new lending which reflect shifts in the distribution of new lending towards borrowers of lower quality.

Our results suggest that, on average over the sample period, small domestic banks significantly increase new loans to high risk borrowers after expansionary monetary policy shocks. The composition of loan supply of small banks shifts towards riskier loans. Although large domestic banks give out more new high risk loans we cannot detect any significant shift in the composition of their loan portfolio. On average over the sample foreign banks lower their exposure to risk. This however mask that especially foreign banks shift their loan supply towards riskier borrowers during the mid-2000s, when interest rates were particularly low for a prolonged period of time ('too-low-for-too-long'). Changes in the risk composition of loan portfolios are not compensated by higher risk premia. Banks rather shift their (new) loan portfolios towards higher risk loans *and* charge a lower risk premium. This is how the risk-taking channel is defined in

²This chapter is based on the paper "In search for yield? Survey based evidence on bank risk-taking" written jointly with Claudia Buch and Sandra Eickmeier (Buch, Eickmeier, and Prieto forth.a).

Borio and Zhu (2012): banks are willing to take on more risk, and this is not compensated by an increase in the risk premium.

The findings of this chapter have some important policy implications. According to the full sample estimation results, concerns about the effect of monetary policy on financial stability might be overstated. Indeed, under normal circumstances it seems that only small banks tend to shift their loan supply towards riskier borrowers. Insofar as small banks are less important in terms of the systemic stability of the financial system our results suggest that central banks should not give too much weight on potential financial stability issues when conducting monetary policy. By contrast, during a prolonged period of low interest rates also foreign banks, which are known to be larger and potentially systemically important, actively engage in risk taking behavior. Hence, the risk-taking channel of monetary policy might become a serious issue for financial stability and as such a concern also for monetary authorities.

CHAPTER 3.³ With this chapter we abandon the assumption of a time-constant relation between the financial sector and the real economy and allow for time variation among these sectors of the economy. Using a Bayesian VAR with time-varying parameters and stochastic volatilities along the lines of Cogley and Sargent (2005) and Primiceri (2005) we address the following fundamental issues: How important is the financial sector as a source of shocks for economic activity? Can we detect changes over time? If, yes, has the propagation of financial shocks to economic activity changed or is it only the size of the shocks which changed? Is the Global Financial Crisis different compared to previous crises? Is the recovery from the Great Recession so weak and slow because of distress in the financial sector?

We find that over the Great Recession period the explanatory power of financial shocks for GDP growth rose to roughly 50 percent, compared to 20 percent in normal times. Among the financial shocks considered, shocks to housing prices were particularly important in explaining the Great Recession, accounting for about 2/3 of the overall contribution of the financial sector to GDP growth. House price and credit spread shocks have been larger and the transmission to growth stronger than previously. The slow and weak recovery from the Global Financial Crisis is mainly because of negative developments in the housing market. A potential reason is that households are still credit constrained. In general, the housing sector affects the macroeconomy asymmetrically:

³This chapter is based on the paper "Time-variation in macro-financial linkages" written jointly with Sandra Eickmeier and Massimiliano Marcellino (Prieto, Eickmeier, and Marcellino 2013).

Negative shocks are more important for the macroeconomy than positive shocks. Moreover, we find a trend increase in the transmission and in the size of housing shocks since the early-2000s, probably due to a rise in housing wealth and the boom in mortgage lending.

Concerning the pre-Global Financial Crisis period, we detect significantly positive contributions of credit spread shocks to GDP growth in the mid-1980s, potentially reflecting the process of financial deregulation. Moreover, we find significantly negative financial shock contributions around the banking crises in the early-1970s (the Bank Capital Squeeze) and in the late-1980s/early-1990s (the Savings and Loan crisis), due to particularly large credit spread shocks and housing shocks. Interestingly the stock market crashes in 1987 and 2001, did not have significantly negative real effects.

CHAPTER 4. Induced by financial innovations and deregulation the past decades have witnessed revolutionary changes in the functioning of the financial system. Until recently there was a strong believe that these changes reduced financial frictions and thereby contributed to a more stable economy. In 2005, Alan Greenspan made this conjecture clear at the Forty-first Annual Conference on Bank Structure "[...]the growing array of derivatives and the related application of more sophisticated methods for measuring and managing risks had been key factors underlying the remarkable resilience of the banking system, which had recently shrugged off severe shocks to the economy and the financial system". With the Global Financial Crisis however the common belief on the merits of a deregulated and complex financial industry was shaken to the very foundations. Instead, today it seems that most of us would agree that the deregulation and all the financial innovations were bad moves.

In this chapter I attempt to uncover the effects of the changes in financial markets on the dynamics of the macroeconomy. In a first step, I estimate a Bayesian VAR with time-varying parameters and stochastic volatilities featuring a standard set of macroeconomic variables and two financial market variables. The time-varying parameter VAR allows to examine potential time-variation in the interaction of the real economy and the financial system. The results from the estimation of the VAR reveal a strong reduction in the correlation of GDP growth with lending. The bulk of this reduction takes place in the early 1980s. In a second step, I estimate key parameters of a DSGE model with financial friction *via* an impulse response matching procedure at different points in time. The results from the structural estimation show that the time variation uncovered in the VAR is mapped into a reduction in the degree of financial frictions over the last decades.

The results summarized above provide strong evidence in support of a reduction in financial friction over the past decades. A careful investigation of the timing of the changes in the dynamic interrelation between real activity and the financial system suggests that the regulatory changes of the early 1980s are likely to be the reason for these changes. By contrast, market driven innovations, such as securitization, and regulatory changes during the 1990s did - if at all - only marginally contribute to the increased stability of the US economy observed in the 1980 and 1990. These results bear important implications for current regulatory proposals as they imply that changes to the regulatory environment as well as most of the new financial product developed over the decade preceding the Great Recession might be much less valuable for the stability of the economy as previously thought and still often claimed.

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Chapter 1

Macroeconomic Factors and Micro-Level Bank Behavior

1.1 Motivation

How are macroeconomic shocks transmitted to individual banks and, in particular, to bank risk? What are the sources of bank heterogeneity, and what explains differences in individual banks' responses to macroeconomic shocks? We provide answers to these questions by analyzing the exposure of banks to macroeconomic developments in the U.S. over the period 1985-2008.

Our analysis is based on a factor-augmented vector autoregressive model (FAVAR) as proposed by Bernanke, Boivin, and Elias (2005). This model extends a standard macroeconomic VAR comprising GDP growth, inflation, house price inflation, and the monetary policy interest rate with a set of factors summarizing a large amount of information from bank-level data. Our bank-level dataset contains two measures of bank risk. The first is the share of non-performing loans in total assets. This ratio informs about changes in the overall quality of the stock of credit and is thus a backward-looking measure of risk. The second is the share of non-interest income in total income, i.e. a flow variable, which is used as a more forward-looking measure of risk (Brunnermeier,

This chapter is based on joint work with Claudia Buch and Sandra Eickmeier entitled "Macroeconomic Factors and Micro-Level Bank Behavior" which is forthcoming in the *Journal of Money, Credit and Banking*.

Dong, and Palia 2012, DeYoung and Roland 2001). The higher the share of non-interest income, the higher the volatility of returns, and thus the higher risk.

We also include bank capitalization, profitability, and bank loans as bank-level variables which affect the transmission mechanism of macroeconomic shocks on risk. Data for a balanced panel of about 1,500 banks are taken from the U.S. Call Reports. We decompose the banking data into common and idiosyncratic components. A set of macroeconomic (supply, demand, monetary policy and house price) shocks is identified, and their transmission through the banking system is assessed. We look at the effects of the shocks on a representative (median) bank and on individual banks. Using cross-sectional regressions, we study which bank-level features can explain differences in banks' responses to macroeconomic shocks.

Our main findings are as follows: (i) Lending by a representative, median bank increases following expansionary shocks. Backward-looking risk tends to decline after expansionary macroeconomic shocks; house price shocks are particularly important. Forward-looking median bank risk increases after expansionary monetary policy shocks. (ii) There is a substantial degree of heterogeneity across banks both in terms of idiosyncratic shocks and the asymmetric transmission of common banking and macroeconomic shocks. Bank size, capitalization, liquidity, risk, and the exposure to real estate and consumer loans matter for risk and lending responses of individual banks to monetary policy and house price shocks.

Our study is related to theoretical and empirical work on the effects of macroeconomic developments on bank risk, which typically focuses on monetary policy shocks. Financial accelerator models imply that changes in interest rates may have countervailing effects on bank risk. On the one hand, lower interest rates might lower risk because the interest rate burden for firms declines and because the value of the underlying collateral increases. Hence, the probability of repayment increases as well. On the other hand, risk might increase because the borrowing capacity of high-risk firms increases with the value of pledgeable assets. Also, banks might engage in riskier, higher yield, projects to offset the negative effects of lower interest rates on profits. Conversely, higher interest rates increase the agency costs of lending, banks reduce the amount of credit to monitoring-intensive firms, and they invest more in safe assets ("flight-to-quality") (Bernanke, Gertler, and Gilchrist 1996, Dell'Ariccia and Marquez 2006, Matsuyama 2007).

While the original financial accelerator models do not assign a specific role to banks, recent macroeconomic models explicitly analyze the feedback between banks and the

macroeconomy in the context of dynamic stochastic general equilibrium (DSGE) models (Angeloni and Faia 2009, Dib 2010, Gerali, Neri, Sessa, and Signoretti 2010, Meh and Moran 2010, Zhang 2009). In these models, the impact of expansionary shocks on bank lending is unequivocally positive, but the impact on bank risk is less clear cut. In Angeloni and Faia (2009), a declining interest rate following a positive supply or an expansionary monetary policy shock, reduces banks' funding costs and increases the probability to repay depositors. To maximize profits, banks optimally choose to increase leverage. But the decline in interest rates also lowers banks' return on assets. This, together with higher leverage, increases bank risk.

In Zhang (2009), to the contrary, expectations of future outcomes play a central role. A positive technology shock, for instance, increases the return on capital over and above its expected value which, in turn, corresponds to a lower than expected loan default rate. The bank thus realizes unexpected profits on its loan portfolio. Bank capital is accumulated through these earnings, strengthening banks' balance sheet positions and reducing risk. A few recent papers also analyze the risk-taking channel of monetary policy and investigate whether low policy interest rates encourage lending to high-risk borrowers due to a "search for yield" (Borio and Zhu 2012, Dell'Ariccia, Marquez, and Laeven 2010, Rajan 2005).

A small set of empirical papers looks at the impact of monetary policy shocks on bank risk. Some studies find evidence that lower interest rates increase bank risk. Ioannidou, Ongena, and Peydro (2009) and Jimenez, Ongena, Peydro, and Saurina (forth.) identify a risk-taking channel for new loans based on loan-level data; Altunbas, Gambacorta, and Ibanez (2009) and Gambacorta (2009) use expected default frequencies for individual banks. Based on time series evidence for the U.S., Angeloni, Faia, and Duca (2010) and Eickmeier and Hofmann (2013) find a decline of various credit risk spreads and an increase of bank balance sheet risk, respectively, following a positive monetary policy shock. Based on data from the Survey of Terms of Business Lending for the US, Buch, Eickmeier, and Prieto (forth.) find that commercial banks shift their lending from low-risk to high-risk borrowers after expansionary monetary policy shocks. Using a model that captures the feedback between bank-level distress and the macroeconomy, De Graeve, Kick, and Koetter (2008), in contrast, find a decline in German banks' probability of distress after a monetary policy loosening. The impact of other shocks has, to the best of our knowledge, not yet been subject to careful empirical investigation, an

exception being Buch, Eickmeier, and Prieto (2011) who find also additional risk-taking by commercial banks after expansionary house price shocks.¹

From a theoretical point of view, the response of bank risk to expansionary shocks differs: the riskiness of new loans and thus risk-taking can be expected to increase while the riskiness of outstanding loans can move either way. The overview of empirical studies confirms that backward-looking risk, which is generally measured using data on outstanding loans, tends to decline after expansionary shocks. By contrast, forward-looking risk measures tend to rise, which is in line with the risk-taking channel.

Our main research question, the exposure of banks to macroeconomic factors, also features prominently in recent proposals for regulatory reforms (Basel Committee 2009). Rochet (2004) shows theoretically that banks should face a capital requirement and a deposit insurance premium that increases with their exposure to macroeconomic factors. Farhi and Tirole (2012) analyze the incentives of banks to coordinate their exposure to macroeconomic shocks. They argue that banks which react more to macroeconomic factors should be regulated more tightly. Gersbach and Hahn (2010) propose a regulatory framework under which a banks' required level of equity capital depends on the equity capital of its peers and, in this sense, on the macroeconomic environment. Implementing these proposals requires information about individual banks' exposures to macroeconomic factors. Our results inform this debate.

We make several contributions. First, the FAVAR model allows analyzing the dynamic interaction between bank-specific and macroeconomic developments in a flexible way. Several VAR-studies allow for the interaction between credit and macroeconomic factors (Ciccarelli, Maddaloni, and Peydro 2010, Eickmeier 2009), but these studies do not focus on bank risk or bank-specific effects. Bank-level studies on the risk-taking or bank lending channel, in contrast, allow macroeconomic factors to affect bank risk, but macroeconomic factors are not modeled as a function of banking variables. Our setup accounts for the endogeneity of both, macroeconomic and banking factors.

Second, the FAVAR allows including a large number of bank-level time series. The model exploits the comovement between individual banks, and it allows us to model linkages between individual banks, running through the interbank market or through the exposure to common shocks. The need to account for linkages between financial

¹Altunbas, Gambacorta, and Ibanez (2009) find that higher GDP growth lowers bank risk but changes in asset prices have no clear-cut impact on risk. The analysis of these factors on risk is, however, not the focus of their paper. Moreover, the authors do not identify structural (real or asset price) shocks.

institutions is one key lesson of the recent crisis (Brunnermeier 2009). Moreover, we model the interaction between different banking variables, including risk and returns of banks. Because we use a large number of bank-level time series, we can assess the exposure of each individual bank to macroeconomic shocks.

Third, previous papers analyzing the bank lending channel or the risk-taking channel regress micro-level variables on the monetary policy interest rate, GDP growth, or asset prices (Altunbas, Gambacorta, and Ibanez 2009, Cetorelli and Goldberg 2012, Ioannidou, Ongena, and Peydro 2009, Jimenez, Ongena, Peydro, and Saurina *forth.*, Kashyap and Stein 2000). These papers address the issue that monetary policy is endogenous by either approximating monetary policy by foreign policy rates (Jimenez, Ongena, Peydro, and Saurina *forth.*) or by Taylor rule gaps (Altunbas, Gambacorta, and Ibanez 2009). The macroeconomic indicators are thus reduced-form constructs, and their developments may reflect the pass-through of different types of shocks. Instead, we consider identified orthogonal macroeconomic shocks which allow us to better disentangle the common drivers of banking sector developments.

Fourth, FAVAR models have previously been fitted to large macroeconomic datasets (Bernanke, Boivin, and Elias 2005, Boivin, Giannoni, and Mojon 2008) or aggregate financial datasets (Nicolo and Lucchetta 2011, Eickmeier and Hofmann 2013). The methodology, however, allows exploiting even richer information, and its application to micro-level data is the natural next step. We will show that omitting bank-level information leads to different estimates of impulse responses and shocks series. Our study is one of the first using a FAVAR model linked to a micro-level dataset. It is closely related to Dave, Dressler, and Zhang (2009) who use a similar modeling approach for U.S. data but focus on the bank lending channel while our focus is on risk. Other papers combining factor models and micro-level data are den Reijer (2011) and Otrok and Pourpourides (2011).

In Sections 1.2 and 1.3, we present the data and the FAVAR methodology, respectively. In Section 1.4, we provide and discuss the empirical results. In Section 1.5, we carry out robustness checks. Section 1.6 concludes.

1.2 The Data

The key feature of our empirical model is the joint analysis of macroeconomic data and bank-level data, which we describe in this section. We also address potential concerns regarding the presence of a factor structure in the data.

1.2.1 Macroeconomic Data

Our set of macroeconomic variables comprises log differences of real GDP, the GDP deflator, real house prices, and the level of the effective Federal Funds rate. Real house prices are measured as the Freddie Mac Conventional Mortgage house price, divided by the GDP deflator. The data are retrieved from FreeLunch.com, a free internet service provided by Moody's Economy.com.

1.2.2 Bank-level Data

Our source for bank-level data is the Consolidated Report of Condition and Income (Call Reports) that all insured commercial banks in the United States submit to the Federal Reserve in each quarter. A complete description of all variables is provided in Table 1.7 in the Appendix. From the Call Reports, we compile a dataset consisting of quarterly income statements and balance sheet data.

Given the turbulences on financial markets in recent years, the choice of the length of the sample is an important issue. We choose a sample which covers the period 1985Q1-2008Q2 and which does not include the period following the bankruptcy of Lehman Brothers. This choice of the pre-crisis sample period is similar to previous work (e.g. Frankel and Saravelos 2012). Using information up to the beginning of the Great Recession in the fourth quarter of 2007 does not qualitatively change our main results. We choose a pre-crisis sample for two reasons. First, this avoids having to deal with possible structural breaks associated with the global financial crisis in a longer sample. Such structural breaks could occur because the magnitude of shocks changes due to multiple credit defaults or multiple financial market segments being hit simultaneously. Structural changes may also occur because of changes in the transmission of shocks. In particular, agency problems between borrowers and lenders tend to be larger in crises than in normal periods. Second, we identify conventional monetary policy shocks to policy interest rates. However, at the end of 2008 monetary policy in the US basically

hit the zero lower bound of interest rates, and the Federal Reserve conducted unconventional monetary policy. Shocks to unconventional monetary policy would be hard to identify, and this would be beyond the scope of our paper.

In terms of bank-level variables, our dataset includes two measures of risk as well as banks' capital ratio, return on assets, and growth of total bank loans. The first measure of risk is the ratio of non-performing loans to total loans.² It captures the asset risk of banks and thus the share of outstanding bank loans that are past due. One advantage of this measure is that it is not much affected by changes in accounting standards. Also, it matches up with theoretical models that describe banks as intermediaries between depositor and lenders and that consider loan defaults as the main source of instabilities in banking (Boyd and Nicolo 2005, Martinez-Miera and Repullo 2010, Zhang 2009).

While the non-performing loans ratio is a backward-looking measure of bank risk, we also use the non-interest income ratio as a more forward-looking measure of bank risk. Existing empirical work suggests that non-interest income generating activities are substantially riskier than traditional credit business (DeYoung and Roland 2001, Stiroh 2006). Furthermore, Brunnermeier, Dong, and Palia (2012) provide evidence that banks with higher shares of non-interest income contribute more to systemic risk than banks with a more traditional business model. Assuming that banks were aware of the risks associated with these investments, we interpret an increase in the non-interest income ratio as evidence of risk-taking by the bank (see also DeYoung, Peng, and Yan 2013).

Preparing the Bank-Level Data for the Factor Analysis

Following previous micro banking studies, we apply a number of screens to exclude implausible and unreliable observations. We exclude observations with (i) negative or missing values for total assets, (ii) negative total loans, (iii) loan-to-assets ratios larger than one, or (iv) capital-to-asset ratios larger than one. Banks with gross total assets below \$25 million are dropped from the sample because they are unlikely to be viable banks (Berger and Bouwman 2009). Also, banks engaged in a merger are omitted. Finally, if one of the three ratios (non-performing loans-to-total loans, capital-to-assets, and net income-to-assets) of an individual bank falls into the bottom or into the top percentile at any point in time, the entire bank is dropped.

²A comparison of the non-performing loans ratio with other measures of (balance sheet and market-based) bank risk used in the literature is provided in the working paper version of this paper (Buch, Eickmeier, and Prieto 2010).

Overall, 13,375 banks have submitted data to the Call Reports at some point in time. After removing implausible values and outliers, 11,466 banks remain in the dataset. Generally, our empirical model requires data from banks operating for a reasonably long time span. For our baseline model, we create a balanced sample of 1,471 banks that are active over the entire sample period. We also analyze the effects of balancing the data by removing banks which operated less than 40 quarters and creating an unbalanced panel of 3,755 banks. Robustness tests presented in Section 1.5 show that results for the balanced and the unbalanced panel are very similar.

The bank-level data are treated in the usual manner for factor analysis. All series are seasonally adjusted, and they enter the dataset as stationary variables. Because loans are assumed to be integrated of order 1, we include them as log differences in our model. The balance sheet ratios can be considered stationary, hence there is no need to difference them. The stationary series are then demeaned, and structural breaks in the means are accounted for.³ Moreover, the series are standardized to have unit variance, and outliers are removed. Outliers are defined as observations with absolute median deviations larger than six times the interquartile range. They are replaced by the median value of the preceding five observations (Stock and Watson 2005).

Is There a Factor Structure in the Data?

Exploiting a rich amount of (bank-level) information can be beneficial in a factor analysis. At the same time, there must be a sufficient degree of co-movement between the individual time series for the factor model to provide a good description of the data. For this to be the case, there needs to be a factor structure among the series included, or, put differently, factors can be accurately estimated only if the series strongly co-move (Boivin and Ng 2006). This issue is particularly relevant for microeconomic data as opposed to (aggregate) macroeconomic data to which factor models have been previously employed and which tend to exhibit a greater comovement.

³Some ratios do not seem to revert to a constant mean. This is possibly due to regulatory changes which led to an adjustment in capital ratios and in other banking variables. To account for these changes, we detect breakpoints by applying the sequential multiple breakpoint test of Bai and Perron (2003) (and the Gauss routines provided by Pierre Perron on his webpage) to all series of our (stationary) dataset, and we subtract the (possibly shifted) means from the series. (See Eickmeier 2009 for a similar treatment of (macroeconomic) data in a factor modelling setup.) When we, instead, linearly detrend the series, the results are basically unaffected.

We first assess to what extent the different banking variables are correlated. Table 1.1 shows that the medians are highly correlated. The non-performing loans ratio and capitalization are strongly (negatively) correlated (0.89) because a decline in asset quality forces banks to write down assets. The correlation is, however, not perfect. Unlike the non-performing loans ratio, capitalization is determined also by regulatory requirements. Moreover, banks use it as a signaling device and might avoid adjustments in response to negative shocks. Furthermore, there is a strong negative correlation between the non-performing loans ratio and the non-interest income ratio. This suggests a possible tradeoff between overall credit risk and risk-taking via non-traditional banking activities.

We, next, examine the co-movement of different banking variables across banks. Table 1.2 shows the variance shares explained by the first 15 principal components extracted separately from bank-level datasets associated with each of the five variables. There is reasonably strong comovement among banks for the non-performing loans ratio, capitalization and the non-interest income ratio with 4 factors explaining at least 30 percent and 6 factors explaining at least 40 percent of the variation in these ratios. The comovement is lower for return on assets and loan growth where 7 and 12 factors are needed to explain 30 percent, respectively.

We have carried out four robustness tests to check the reliability of our banking factors. First, we have removed cross-sectional outliers from the dataset, i.e. we have dropped banks from the sample with absolute median deviations larger than six times the interquartile range (on average over the sample period). This procedure identifies about 300 series as outliers.

Second, using weighted principal components (Boivin and Ng 2006), we have down-weighted each bank-level series by the inverse of the standard deviation of its idiosyncratic component.

Third, we have aggregated the balance sheets of all banks that belong to the same bank holding company. This alternative dataset contains 556 bank holding companies, and we have extracted factors from this dataset. The reason is that bank holding companies may be able to shift resources among the banks they control (Kashyap and Stein 2000), and we would expect the comovement between bank holding companies to be larger than that between individual banks. The factors extracted from our original dataset and the factors estimated in these robustness checks are very highly correlated. The trace R^2 from a regression of the principal components extracted from the original

dataset on the principal components estimated from the modified datasets lie between 0.97 and 0.99.⁴

Fourth, we have assessed whether omitting state-level banking factors affect our estimation of the national factors. We have separately extracted factors from the bank-level data state-by-state using principal components. We have then pooled the state-level factors and estimated national factors from the pooled dataset. (See Beck, Hubrich, and Marcellino 2009, Del Negro and Otrok 2007, Kose, Otrok, and Whiteman 2003, or Mönch, Ng, and Potter forth. for alternative approaches).⁵ The trace R^2 from a regression of the principal components extracted from the entire dataset on the principal components extracted from the set of state-level factors is, again, very high (0.99). Hence, neglecting regional factors at a first estimation stage does not seem to affect our nation-wide factor estimates. We note that this does not mean that regional banking factors are not important. If regional banking developments have nation-wide macroeconomic effects the contributions of shocks to the (nation-wide) banking factors to the macroeconomic variables that we will examine below will give us an estimate of the lower bound of the overall influence of the banking sector on the macroeconomy.

1.3 The FAVAR Methodology

With the bank-level variables at hand, we next describe how we use this information to model the dynamic feedback effects between individual U.S. banks and the macroeconomy. We start from a small-scale macroeconomic VAR model which includes GDP growth (Δy_t), GDP deflator inflation (Δp_t), the Federal Funds rate (ffr_t), and real house price inflation (Δhp_t) as endogenous variables. These variable are summarized in an $M(=4)$ -dimensional vector $G_t = [\Delta y_t \Delta p_t \Delta hp_t ffr_t]$. GDP growth, inflation, and interest rates represent the standard block of variables included in macroeconomic VARs (Christiano, Eichenbaum, and Evans 1996, Peersman 2005); fewer studies also include house prices (Bjørnland and Jacobsen forthcoming, Jarocinski and Smets 2008).

⁴The comparison is based on the first 6 principal components because 6 latent factors are also used in our analysis below. Below, we will explain this choice of the number of factors.

⁵More precisely, out of the 50 states in the U.S. we consider only the states with at least 10 banks (which would result in at least 40 series per state). This leaves us with 40 states. We estimate the state-level factors as the first 6 principal components from bank-level data for each of the 40 states. We pool the estimated state-level factors, extract the first 6 principal components from the 240 ($=6 \times 40$) state-level factors, and compare them with the first 6 principal components estimated from the entire dataset.

We augment the vector G_t with a set of "banking factors" B_t which yields the $(r + M) \times 1$ -dimensional vector $F_t = [G_t' H_t']$. The vector of banking factors $B_t = [b_{1t} \dots b_{rt}]$ is unobserved and needs to be estimated.

We model the joint dynamics of macroeconomic variables and banking factors as a $VAR(p)$ process:

$$A(L)F_t = c + Pw_t, \quad (1.3.1)$$

where $A(L) = I - A_1L - \dots - A_pL^p$ is a lag polynomial of finite order p , c comprises constants, and w_t is a vector of structural shocks which can be recovered by imposing restrictions on P .

Let the elements of F_t be the common factors driving the $(N \times 1)$ vector X_t which summarize our five banking variables of 1,471 individual banks. To assess the impact of macroeconomic shocks on the "average" bank, we also include in X_t the medians of the five banking variables.⁶ Hence, the cross-section dimension is $N = 7,360 (= 1,471 \times 5 + 5)$.

It is assumed that X_t follows an approximate dynamic factor model (Bai and Ng 2002, Stock and Watson 2002):

$$X_t = \Lambda' F_t + \Xi \quad (1.3.2)$$

where $\Xi = [\xi_{1t} \dots \xi_{Nt}]$ denotes a $(N \times 1)$ vector of idiosyncratic components.⁷ The matrix of factor loadings $\Lambda = [\lambda_1 \dots \lambda_N]$ has dimension $(r + M) \times N$, λ_i $i = 1 \dots N$ is of dimension $(r + M \times 1)$, and $r + M \ll N$ holds. Common and idiosyncratic components are orthogonal, the common factors are mutually orthogonal, and idiosyncratic components can be weakly mutually and serially correlated in the sense of Chamberlain and Rothschild (1983). Equations (1) and (2) represent a FAVAR model as has been introduced by Bernanke, Boivin, and Elias (2005).⁸

The model is estimated in five steps.

First, the dimension of F_t , i.e. the overall number of common factors $(r + M)$, is determined to be 10. These include the 4 observable macroeconomic factors and the

⁶To save time and capacity, we will compute confidence bands only for these median variables but we will focus on point estimates for individual banks' responses. Point estimates of median impulse response functions are very similar to point estimates of impulse response functions of the median bank.

⁷Note that F_t can contain dynamic factors and lags of dynamic factors. Insofar, equation (2) is not restrictive.

⁸Bernanke, Boivin, and Elias (2005) are interested in a monetary policy shock and include the Federal Funds rate as the only observable in the FAVAR. Our model most closely resembles the one used in Eickmeier and Hofmann (2013) which models a set of latent factors estimated from non-financial sector balance sheet items and other financial variables.

$r = 6$ latent banking factors. We make this choice because our main results change when the number of factors is lowered, but are barely affected when it is increased, and because we prefer a sparse parametrization. This approach has been applied also by Boivin, Giannoni, and Mojon (2008).

Second, we estimate B_t by removing the observed factors from the overall factor space. We do this using the iterative procedure proposed by Boivin and Giannoni (2007). We obtain an initial estimate of B_t , \hat{B}_t^0 , as the first $r = 6$ principal components of X_t . Then, we regress X_t on \hat{B}_t^0 and G_t , ending up with $\hat{\Lambda}_G^0$, the coefficients (or factor loadings) that belong to G_t . We calculate $\hat{X}_t^0 = X_t - \hat{\Lambda}_G^0 G_t$ and estimate \hat{B}_t^1 as the first r principal components of \hat{X}_t^0 . This procedure is repeated until convergence, and we end up with the estimator of B_t , \hat{B}_t .⁹ The latent banking factors, together with the observable macroeconomic factors, explain 46 percent of the variation in the bank-level dataset which represents a reasonable degree of comovement between the banking variables.

Third, a $VAR(1)$ model is fitted to $[G_t' \hat{B}_t']'$. The lag order of 1 is suggested by the Bayes Schwarz information criterion (BIC).

Fourth, we identify macroeconomic shocks combining sign restrictions and zero contemporaneous restrictions, as will be explained shortly. In the fifth and final step, confidence bands of the impulse response functions are constructed using the bootstrap-after-bootstrap technique proposed by Kilian (1998). This technique allows removing a possible bias in the VAR coefficients which can arise due to the small sample size. The number of bootstrap replications equals 500. Notice that, since $N \gg T$, we neglect the uncertainty involved with the factor estimation (and hence, the estimation of the idiosyncratic components), as suggested by Bernanke, Boivin, and Elias (2005).

As regards the identification of macroeconomic shocks in step four, we apply sign restrictions on short-run impulse response functions (Canova and de Nicolò 2003, Faust 1998, Peersman 2005, Uhlig 2005) and contemporaneous zero restrictions. The identification scheme is implemented in two steps. The first step involves carrying out a Cholesky decomposition of the covariance matrix of the reduced form VAR residuals. We impose the following ordering: $\Delta y_t \rightarrow \Delta p_t \rightarrow \Delta h p_t \rightarrow \hat{B}_t \rightarrow f f r_t$. We label the Cholesky residuals associated with the equations explaining house price inflation, the r latent banking factors' and the Federal Funds rate "house price shock", "shocks to the

⁹We define the procedure as having converged if the sum of squared residual from a regression of x_{it} $i = 1, \dots, N$ on $\hat{B}_t^{(j)}$ and G has hardly changed compared to the sum of squared residual from a regression of x_{it} on $\hat{B}_t^{(j-1)}$ and G (by no more than a small value which we shall set at 0.000001).

banking factors” (or ”banking shocks”), and ”monetary policy shocks”, respectively. We cannot be sure that the shocks to the banking factors truly represent shocks that occur in the banking sector or ”banking shocks”. They may instead also contain shocks that are not modeled explicitly, such as shocks to balance sheets of the non-financial private sector (which may, however, also be propagated through the banking system).

The second step aims at disentangling ”aggregate supply shocks” and ”aggregate demand shocks”. It involves rotating the Cholesky residuals associated with the equations for GDP growth and GDP deflator inflation and imposing theoretically motivated sign restrictions. After an aggregate supply shock, GDP and the GDP deflator move in opposite directions. After an aggregate demand shock, these two variables as well as the Federal Funds rate move in the same direction. The sign restrictions are imposed contemporaneously and on the first four lags after the shock. Results are robust with respect to the restricted number of lags. The identifying restrictions are summarized in Table 1.3. In the Appendix, we explain how we identify the shocks in more detail.

The sign restrictions are consistent with standard theoretical models (Peersman 2005). The ordering implies that GDP as well as aggregate and house prices do not react contemporaneously to banking and monetary shocks, which is fairly standard in SVAR studies (Christiano, Eichenbaum, and Evans 1996, Ciccarelli, Maddaloni, and Peydro 2010, Eickmeier and Hofmann 2013, Nason and Tallman 2012, Peersman 2012). GDP and the overall price level react with a delay to house price movements (Jarocinski and Smets 2008). While it is relatively common to use a Cholesky decomposition to identify housing shocks (Giuliodori 2005, Iacoviello 2005), alternative identification schemes for the house price shock such as sign restrictions (Jarocinski and Smets 2008) or a combination of zero contemporaneous and long-run restrictions (Bjørnland and Jacobsen forthcoming) have also been used in the literature. As we discuss below, they yield similar results. Moreover, we allow the monetary policy instrument to respond contemporaneously to all shocks.

Ordering the monetary policy rate below the banking factors is somewhat controversial. We follow most of the SVAR literature which jointly models macroeconomic and banking variables (Ciccarelli, Maddaloni, and Peydro 2010). Reasons for sluggish adjustment of the banking sector to monetary policy could be the need to renegotiate existing contracts or close customer relationships that banks do not want to interrupt. Consistent with this assumption, the empirical banking literature finds that interest rate spells of banks are sticky and do not react quickly to market interest rates (Berger and

Hannan 1991). We emphasize that, although the banking factors are restricted to respond to the monetary policy shocks with a delay, individual banks' variables can react immediately to the monetary policy shocks. Insofar, ordering the banking factors above the monetary policy rate is not very restrictive. We will show below that shapes and signs of the impulse responses of macroeconomic variables after the monetary policy shocks are very plausible, lending further support to our identification approach. Moreover, we will assess robustness regarding the ordering of banking factors and the monetary policy rate.¹⁰

1.4 Empirical Results

We organize the presentation of our empirical results around our two main research questions. We begin with the question how macroeconomic shocks are transmitted to the banking sector, and we subsequently explore heterogeneity across banks.

1.4.1 How are Macroeconomic Shocks Transmitted to the Banking Sector?

Impulse Response Functions of Macroeconomic Variables

Before exploring how macroeconomic shocks are transmitted to banks, we need to analyze whether our model generates plausible adjustment patterns for the macroeconomic time series. Figure 1.1 thus plots the impulse response functions of (the levels of) GDP, the GDP deflator, house prices, and the Federal Funds rate to aggregate supply, aggregate demand, monetary policy, and house price shocks. We show median responses together with 90% confidence bands to shocks of the size of one standard deviation.

Supply and demand shocks have the expected effects. After a supply shock, GDP rises and the GDP deflator falls permanently. The demand shock triggers a temporary increase in GDP, and the general price level rises permanently. The monetary policy rate does not change significantly after the supply shock, but it rises temporarily after the demand shock.

Expansionary monetary policy shocks lead to a temporary rise in economic activity (consistent with long-run real neutrality of monetary policy) and to a permanent rise in the GDP deflator. We do not observe a price puzzle, i.e. a decline of the price level after

¹⁰We thank an anonymous referee for suggesting this robustness check.

an expansionary monetary policy shock. This is reassuring because it suggests that we have accurately identified monetary policy shocks.

House price shocks trigger responses which are reminiscent of demand shocks: Economic activity, the general price level, and the monetary policy rate rise. The increase in GDP shortly after the house price shock is, however, not statistically significant. The (temporary) decline in GDP can be explained by its reaction to the monetary policy tightening observed after the house price shock. House prices rise more than the general price level. This overall pattern for the house price shock confirms that house price shocks are well identified (sign restrictions would essentially deliver the same results).¹¹ House prices react sluggishly to macroeconomic shocks. Their reaction roughly mirrors the reaction of the GDP deflator.

Impulse Response Functions of Banking Variables

To assess the dynamic transmission of macroeconomic shocks to the banking sector, we look at impulse response functions for the median bank (Figure 1.2). In line with theory, bank loans increase after all expansionary shocks, including expansionary monetary policy shocks. This is in line with the credit channel of monetary policy.

The response of bank risk to expansionary shocks depends on the risk measure used and the type of shock considered. Our backward-looking risk measure (the non-performing loans ratio) declines following monetary policy, demand, and house price shocks. The effects last between two quarters (after the demand shock) and about four years (after the monetary policy shock). In terms of magnitudes, the economic effect of the monetary policy shock on the non-performing loans ratio is quite small though: a decline in the Federal Funds rate by 15 basis points lowers the ratio by about 0.008 percentage points. This corresponds to a 0.9 percent reduction relative to the average non-performing loans ratio, which is around 1 percent.

¹¹We formally test this by rotating the orthogonalized (Cholesky) residuals associated with the GDP growth, inflation and house price inflation equations (and not only, as before, the residuals associated with the GDP growth and inflation equations). We then impose the same restrictions for the aggregate supply and demand shocks and some additional restrictions to identify the house price shock (which we interpret as a housing demand shock) and to separate it from an aggregate demand shock, as follows. After the housing demand shock, GDP increases, house prices increase, and house prices relative to the general price level increase. After the aggregate demand shock, house prices now increase by less than the general price level. Impulse responses of macroeconomic variables and median banking variables after the identified housing demand shock are almost identical to corresponding impulse responses after the house price shock identified in our baseline specification.

The decline in non-performing loans in response to a monetary policy shocks is in line with the prediction in Zhang (2009) who argues that an expansionary monetary policy shock increases credit supply by reducing funding costs. Ex post loan default rates go down, which feeds back into better capitalization. The decline in non-performing loans following a demand shock can be explained by the fact that the increase in GDP strengthens borrowers' balance sheets. Monetary policy reacts to the demand shock by raising interest rates, which can explain the subsequent increase in the share of non-performing loans. As credit risk increases, the response of loans starts to decline and becomes insignificant after about six quarters. In contrast, the non-performing loans ratio increases in response to supply shocks. Following a positive supply shock, the balance sheet composition of banks tilts towards higher leverage (a lower capital-to-asset ratio) and higher credit risk, which is consistent with Angeloni and Faia (2009). Turning to our second risk measure, the non-interest income ratio, gives results which differ from those for the non-performing loans ratio. After expansionary monetary policy shocks, the non-interest income ratio increases by a small amount (0.01 percentage points). Because the non-interest income ratio is a flow measure of risk and thus more forward looking, this suggest that banks take on additional risk after a decline in the monetary policy rate. The non-interest income ratio of the median bank does not change significantly after the house price shocks, and it declines after the other two macroeconomic shocks.

Our result of a decline in the share of non-performing loans after expansionary monetary policy shocks is similar to the findings by De Graeve, Kick, and Koetter (2008). Our finding of a rise in forward-looking risk is consistent with the risk-taking channel literature.

The impulse response analysis also reveals that the negative correlation between the non-performing loans ratio and the non-interest income ratio observed in the raw data is mainly driven by monetary policy shocks (and to a lesser extent by supply shocks). Furthermore, the correlation between bank returns and the non-interest income ratio is negative for all shocks but house price shocks. This pattern is in line with the search for yield hypothesis that banks try to generate higher profits by increasing their exposure to riskier non-traditional banking activities when interest rates (and thus returns) and credit risk are low.

Variance Decompositions

In order to answer the question how relevant the macroeconomic shocks are for banking sector developments, Table 1.4 shows the forecast error variance decomposition.¹² We distinguish the short run (the one-year forecast horizon) from the medium run (the five-year horizon). In the short run, all macroeconomic shocks together explain more than 20 percent of bank risk and of the capital ratio and 16 and 9 percent of returns on assets and loans, respectively, of the median bank. These numbers increase by up to 6 percentage points in the medium run. The numbers for loans seem relatively small, but are consistent with the variance decomposition findings by Christiano, Motto, and Rostagno (2010) for US real credit.

Looking at individual macroeconomic shocks, demand and house price shocks are most important for the non-performing loans ratio and thus for backward looking bank risk. Because real estate serves as collateral for loans, movements in house prices affect the quality of collateral and thus the strength of borrowers' balance sheets. Moreover, the exceptional housing boom in the 2000s, which was associated with an increase in (subprime) lending, falls into our sample.

Monetary policy shocks also explain a non-negligible fraction of variation in non-performing loans (5 percent) in the medium run. For the non-interest income ratio, supply and demand shocks are the most important macro shocks. Although we find an increase of risk-taking after an expansionary monetary policy shock, the overall role played by monetary policy shocks seems to be small. Aggregate supply shocks account for the greatest share of the variation in loans at short and medium horizons. Moreover, the idiosyncratic (variable-specific) components are at least as important as common banking shocks.

Table 1.4 also reveals that shocks to the latent banking factors (or "banking shocks") are quite important for macroeconomic variables. This holds especially for the Federal Funds rate, indicating that monetary policy, directly or indirectly, via the impact of banking shocks on output growth and inflation, reacts to banking shocks. The banking shocks also account for more than 20 percent of the variance of GDP and house prices in the medium run.

¹²The full variance decomposition has been carried out based on an AR(1) model which we fit to the idiosyncratic components.

The Role of Bank-Level Information

The empirical results presented so far assume that bank-level information is important for modeling macroeconomic dynamics. But how important is the micro-level banking information for our results? To answer this question, Figure 1.3 compares the impulse responses of the observable macroeconomic factors derived from our benchmark FAVAR model with impulse responses obtained from a VAR in which we replace the banking factors by the median values of our banking variables. The responses of GDP, the GDP deflator, and house prices following macroeconomic shocks are very similar in magnitude and shape. There are, however, some differences in the responses of the Federal Funds rate after all four shocks: The VAR model without micro-level information predicts larger and more persistent responses of the interest rate relative to our benchmark FAVAR model. The reason could be that the banking sector cushions the effects of macroeconomic shocks and that, in this case, monetary policy needs to react less to shocks to stabilize the economy than if an active banking sector was not fully captured. It is therefore not surprising that the model which omits relevant information contained in the micro banking data suggests a stronger monetary policy reaction than our baseline model.

In addition, monetary policy shocks identified from the VAR model with the median banking variables are larger than the shocks extracted from the benchmark FAVAR (Figure 1.4). This suggests that the VAR model assigns shocks originating in the banking market to monetary policy.¹³ We have also compared a VAR with the five median banking variables with a VAR which includes only the four macroeconomic variables. Findings are almost identical, and we do not show results from the pure macroeconomic VAR here. Hence, information contained in the micro bank-level data seems to matter.

1.4.2 What are the Sources of Heterogeneity across Banks?

So far, we have focused on adjustments of the "median" bank following macroeconomic shocks. However, the rich structure of our dataset also allows analyzing bank heterogeneity. Bank heterogeneity has two dimensions: There are idiosyncratic components in bank-level developments, and heterogeneity may also reflect different responses of banks to the common shocks. Next, we analyze the importance of these sources of hetero-

¹³We omit the identified supply, demand and house price shock series because they are very similar in both models.

geneity by looking at the dispersion of the common and the idiosyncratic components of bank-level developments. In a final step, we will use information on bank characteristics to explain different adjustments to macroeconomic shocks.

Idiosyncratic Shocks versus Asymmetric Transmission of Common Shocks

Table 1.5 shows the dispersion of idiosyncratic and common components of individual banks' variables. Comparing the rows of this table shows that bank heterogeneity is not only due to idiosyncratic shocks but also due to the asymmetric transmission of common shocks. For all variables but the capital and non-interest income ratios, asymmetric transmission of common shocks is more important.

To visualize the transmission of common macroeconomic shocks to individual banks, Figure 1.5 shows the 5th to 95th quantiles of impulse response functions of individual banks. The graph reveals substantial heterogeneity after all macroeconomic shocks, in line with results by Dave, Dressler, and Zhang (2009) for the development of loans after monetary policy shocks. Although the non-performing loans ratio (the non-interest income ratio) has been shown to decline (increase) for the median bank in response to an expansionary monetary policy shock, Figure 1.5 shows that this does not hold for a large fraction of banks: the ratio of non-performing loans to total loans increase for about 1/3 of banks in response to an expansionary monetary policy shock; the ratio of non-interest income falls for about 2/5 of all banks.

Which Bank-Level Features Affect the Exposure of Banks to Monetary Policy and House Price Shocks?

In a next step, we analyze whether the impact of monetary policy and house price shocks differs across individual banks in any systematic way. We regress individual banks' impulse response functions of our two risk measures and lending on several variables capturing long-run structural differences across banks. We also distinguish the responses after two and four quarters.

We focus on monetary policy and house price shocks for three main reasons: First, house price shocks play a prominent role in theoretical studies featuring financial accelerator mechanisms (Kiyotaki and Moore 1997). Changes in house prices affect collateral values, hence banks which are more affected by information asymmetries or which have a business model geared towards retail lending should be affected more. Second, we have

shown that house price shocks are important for bank risk. Third, the reaction of banks to changes in monetary policy has been the subject of many empirical studies allowing us to compare our results (Cetorelli and Goldberg 2012, Gambacorta and Mistrulli 2004, Kashyap and Stein 2000, Kishan and Opiela 2000).

Our explanatory variables are size, internationalization, liquidity, connectedness with other banks via the interbank market, riskiness, capitalization, and differences in banks' loan portfolio structure. (See the Appendix for details.) To account for the skewed size distribution in the banking sector and possible non-linearities in the response to shocks, we also square the size variable. In addition, we add a full set of state dummies (unreported). Because the bank-level features capture structural differences across different types of banks, they are averaged over the sample period. We check the robustness of our results by dropping individual regressors. In unreported regressions, we find that the main results are not affected.

We estimate the model with OLS and apply heteroscedasticity-robust standard errors. All explanatory variables (except for the dummy variables) are demeaned. The constant can therefore roughly be interpreted as the average effect, and the coefficient estimates should be interpreted relative to the constant. The regression results are presented in Table 1.6, and we emphasize only results which are robust in the sense that they hold for both the two- and the four-quarter horizons.

We expect that small banks are more affected by macroeconomic shocks than large banks because of lower net worth, lack of diversification, and less diversified funding (Diamond and Rajan 2006, Kashyap and Stein 2000). In line with this, lending by small banks increases by more than lending by large banks after expansionary monetary policy and house price shocks. The impact of size levels off as banks grow larger. Size has no significant impact on the response of non-performing loans to monetary policy shocks. However, larger banks react relatively less strongly in terms of their non-interest income generating activities.

Better access to liquidity should reduce banks' exposure to shocks affecting funding conditions (Diamond and Rajan 2006). Liquidity has a robust effect only in the non-interest income equation after house price shocks: more liquid banks reduce their non-traditional banking activity by less than less liquid banks.

Internationalization of banks could affect their exposure to shocks. If shocks at home and abroad are imperfectly correlated, the presence of foreign affiliates might activate a channel of diversification, thereby reducing the response to domestic shocks. Cetorelli

and Goldberg (2012) show that internationally oriented banks have the potential to lay off domestic macroeconomic shocks through an internal capital market. Yet, we do not find a robust effect of internationalization on the reaction of banks to the shocks examined. Also, banks' exposure to the interbank market (Allen and Gale 2001) has no robust impact on their response to macroeconomic shocks.

Risk, measured as the non-performing loans ratio averaged over the sample period, and capitalization do not affect the lending responses of banks.¹⁴ But better capitalized banks and banks with higher average level of credit risk increase their share of non-interest income and thus new risk less after monetary policy shocks. This corresponds well with the negative correlation between the impulse responses of these two risk measures to monetary policy shocks. Similarly, better capitalization dampens the response of the non-interest income ratio after house price shocks. Moreover, the riskier banks are, the stronger the effect of house price shocks on the non-performing loans ratio.

Finally, bank lending increases more in response to an expansionary house price shock if banks are highly exposed to real estate and consumer loans. One explanation is that, after negative house price and monetary tightening shocks, a decline in (house price) inflation increases the real value of debt obligations by borrowers, reduces collateral value, and limits resources available to borrowers (Gerali, Neri, Sessa, and Signoretti 2010). Furthermore and quite intuitively, banks with a business model geared towards real estate lending have lower exposure to non-traditional banking activity following monetary easing.

1.5 Robustness Analysis

1.5.1 The Effects of Balancing the Panel

Results presented so far are based on a balanced panel which contains only banks with a full string of time series information.¹⁵ Balancing the panel involves a trade off. On the one hand, balancing the panel might induce a selection bias which can occur if we systematically drop banks with specific characteristics and behaviors. On the other hand, it would also be problematic to include banks in our sample which are systematically

¹⁴This is in contrast to Kishan and Opiela (2000) and Gambacorta and Mistrulli (2004) who find that capitalization is an important determinant of banks ability to shield their loan portfolio from a tightening of monetary policy.

¹⁵We are grateful to our anonymous referees for suggesting this robustness analysis to us.

different and to apply the same model to all banks. Because there is no optimal approach to cope with this problem, we now compare the results for the balanced and for the unbalanced panel.

This comparison begins with the unconditional distributions of the time series observations of banks across the different samples (Figure 1.6). We compare the full sample (11,466 banks), the unbalanced sample (3,755 banks), and the balanced panel used for our baseline results (1,471 banks) (see Section 1.2.2). Figure 1.6 shows that general patterns of the data are similar in all three panels. The main difference between the balanced panel and the unbalanced panel is that the former does not include banks which defaulted before the end of the sample period and banks that started operating after 1985. Even if these two groups were very different, the group of all banks together that were dropped seems to have characteristics comparable to those of the group of banks that we kept in our balanced sample. The distributions of variables in the balanced and unbalanced panels are also similar to those in the full panel.

Yet, even if unconditional distributions are similar, the distributions of impulse responses to the macroeconomic shocks might differ. There are methods to deal with unbalanced panels in factor models. It is important to note, however, that these methods rely on the assumption that observations are "missing at random". One approach has been suggested by Connor and Korajczyk (1987) (see also Korajczyk and Sadka 2008 for a discussion). It involves applying principal components to a covariance matrix of which element i, j is the covariance between series i and series j over the period in which they overlap. We repeat our FAVAR analysis applying that approach to the unbalanced panel.¹⁶ We look at the distribution of the banks' impulse responses to the macroeconomic shocks, and we also regress impulse responses of individual banks on banks' characteristics. To save space, we provide only the median bank's impulse responses to the macroeconomic shocks (Figure 1.7), but we make the other results available upon request.

The factor space estimated from the unbalanced panel is very similar to the one estimated from the balanced panel (trace R^2 : 0.90). Also, the median banks' responses are very similar to those in our baseline. Except for some impact effects, confidence bands overlap. From the second quarter onwards, impulse responses are almost identical. In

¹⁶Another method is the expectations maximization (EM) algorithm suggested by Stock and Watson (1998) and Stock and Watson (2002) which involves interpolating the missing data exploiting the factor model iteratively. We use the Connor and Korajczyk (1987) method which is faster than the iterative EM algorithm, and because we had problems reaching convergence with the EM algorithm.

addition, the entire distribution of individual banks' responses to the macroeconomic shocks is very similar in both models. We only note that the reactions of banks from the unbalanced panel to the shocks are somewhat more heterogeneous than the reactions of banks from the balanced panel. Regression results are very robust as well, except that for impulse response after four quarters some explanatory variables become less significant. This is not because of different factor estimates but because of less precisely estimated coefficients. Overall, we interpret these results as evidence that sample selection issues do not invalidate our main results.

1.5.2 Sensitivity with Respect to the Identification Scheme

The banking factors have so far been identified pooling all banking variables. But it could be argued that bank risk is, compared to the other banking variables, rather fast moving. Hence, it might be inappropriate to restrict all common banking factors to respond with a delay to changes in the monetary policy rate. We therefore extract a separate factor from both bank risk variables and order the "risk factor" below the monetary policy rate which allows it to react immediately to interest rate movements. The other banking factors are ordered, as before, above the policy rate.

Impulse response functions of the median bank to the macroeconomic shocks are shown in Figure 1.8. The short-term reaction of the non-interest income ratio is larger than in the baseline (the signs are the same) which can possibly be explained by the fact that the risk factor can now respond on impact to the monetary policy (which makes it more likely that median bank's risk also reacts instantaneously). Otherwise, results are very similar. We also extract, alternatively, a separate risk factor only from our forward-looking risk measure (the non-interest income ratios), proceed as just described and reach identical conclusions.

1.6 Concluding Remarks

In this paper, we use a FAVAR model to analyze feedback effects between banks and the macroeconomy. We focus on the heterogeneous exposure of U.S. banks to macroeconomic factors, and we make several contributions to the literature. First, we model the dynamic interaction of macroeconomic and banking factors. Second, we allow for and exploit the linkages between individual banks and between different banking variables such as bank lending, risk, and return. Third, we identify orthogonal macroeconomic shocks to cleanly

decompose banks' common risk into its different sources, and we isolate these shocks from idiosyncratic risk at the bank level.

We are now in the position to answer the questions raised at the beginning of the paper.

(i) How are macroeconomic shocks transmitted to bank risk and other banking variables?

Macroeconomic shocks have an important impact on bank risk and on other bank-level variables. Bank lending of a representative (median) bank increases following expansionary shocks, consistent with an increased demand for investment and working capital loans during boom periods or an increased credit supply. The response of bank risk depends on the measure of risk used. Non-performing loans of the median bank and thus backward-looking risk decline after expansionary macroeconomic shocks with the exception of supply shocks. The median bank increases forward-looking risk, measured through the share of non-interest income, following expansionary monetary policy shocks.

Shocks to the banking factors also matter for the macroeconomy. In the medium term, these shocks explain more than 15 percent of macroeconomic volatility. Their explanatory power is highest for the monetary policy interest rate and for house prices. Omitting bank-level information can yield misleading estimates of impulse responses and monetary policy shocks.

(ii) What are the sources of bank heterogeneity, and what explains differences in individual banks' responses to macroeconomic shocks?

There is a substantial degree of heterogeneity across banks both in terms of idiosyncratic shocks and the asymmetric transmission of common (banking and macroeconomic) shocks. While the share of non-performing loans declines for the median bank, risk of about 1/3 of all banks rises in response to an expansionary monetary policy shock. The share of non-interest income increases for the median bank, but it declines for about 2/5 of the banks. We have also studied which bank-level features can explain differences in banks' exposure to expansionary monetary policy shocks. Size, the degree of capitalization, liquidity, riskiness and the exposure to real estate and consumer loans were found to matter for risk and lending responses of banks to monetary policy and house price shocks.

Our findings are interesting from a banking regulation perspective. Our results lend support to proposals that higher capital and higher liquidity requirements can enhance

the resilience of the banking sector to macroeconomic shocks. Also, smaller banks are more exposed to macroeconomic risk but, at the same time, the systemic impact of these banks on the macroeconomy is rather small. Regulatory policy thus needs to balance different criteria such as the relevance of an institution for systemic risk and its exposure to macroeconomic shocks when deciding upon new capital or liquidity requirements.

Overall, our analysis can be seen as a first step into the direction of jointly modeling dynamics of the banking sector and the macroeconomy. It suggests that these feedback effects are relevant for both, understanding macroeconomic dynamics as well as the behavior of banks. Research of this type would certainly benefit from high-quality microeconomic panel data.

1.7 References

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1.8 Tables and Figures

Table 1.1: Correlation between Median Banking Variables

	Non-performing loans/total loans	Equity capital/ assets	Return on assets	Change in loans	Non-interest income/ net operating income
Non-performing loans/loans	1				
Equity capital/assets	-0.89	1			
Return on assets	-0.41	0.46	1		
Change in loans	-0.33	0.29	0.46	1	
Non-interest income /net operating income	-0.64	0.67	-0.081	-0.23	1

Table 1.2: Cumulated Variance Shares Explained by the First 15 Principal Components Calculated from Datasets Associated with Individual Banking Variables

	Non-performing loans/total loans	Equity capital/ assets	Return on assets	Change in loans	Non-interest income/ net operating income
1	0.14	0.22	0.07	0.05	0.13
2	0.21	0.36	0.12	0.08	0.22
3	0.28	0.47	0.16	0.12	0.3
4	0.34	0.54	0.2	0.14	0.38
5	0.39	0.61	0.23	0.17	0.44
6	0.43	0.66	0.27	0.19	0.48
7	0.47	0.7	0.3	0.21	0.52
8	0.5	0.73	0.32	0.23	0.56
9	0.52	0.75	0.35	0.25	0.59
10	0.55	0.78	0.37	0.27	0.62
11	0.58	0.79	0.39	0.29	0.64
12	0.6	0.81	0.42	0.31	0.67
13	0.62	0.82	0.44	0.33	0.69
14	0.63	0.83	0.45	0.34	0.71
15	0.65	0.84	0.47	0.36	0.73

Table 1.3: Identifying Restrictions

	Supply shocks	Demand shocks	House price shocks	Monetary policy shocks	Shocks to latent (banking) factors
GDP	+	+	0	0	0
GDP deflator	-	+	0	0	0
House price				0	0
Federal Funds rate		+			
Banking factors				0	

Table 1.4: Forecast Error Variance Decomposition

	Supply shocks	Demand shocks	House price shocks	Monetary policy shocks	Shocks to latent (banking) factors	Idiosyncratic shocks
1-year horizon						
GDP	0.55	0.31	0.01	0.00	0.08	
GDP deflator	0.55	0.33	0.03	0.01	0.03	
House price	0.03	0.02	0.82	0	0.08	
Federal Funds rate	0.02	0.38	0.13	0.07	0.34	
Non-performing loans / loans	0.05	0.06	0.12	0.01	0.26	0.47
Equity capital / assets	0.03	0.24	0.03	0.01	0.21	0.45
Return on assets	0.11	0.04	0.01	0	0.07	0.76
Loans	0.05	0.02	0.02	0	0.06	0.84
Non-interest income ratio	0.08	0.11	0.01	0.01	0.36	0.38
5-year horizon						
GDP	0.47	0.11	0.05	0.01	0.24	
GDP deflator	0.49	0.23	0.02	0.03	0.13	
House price	0.03	0.04	0.5	0.01	0.28	
Federal Funds rate	0.03	0.31	0.13	0.07	0.38	
Non-performing loans / loans	0.05	0.1	0.1	0.05	0.35	0.3
Equity capital / assets	0.03	0.21	0.04	0.03	0.34	0.29
Return on assets	0.1	0.05	0.02	0.01	0.14	0.67
Loans	0.05	0.02	0.01	0.02	0.25	0.58
Non-interest income ratio	0.08	0.10	0.03	0.03	0.43	0.27

Table 1.5: Dispersion of Common and Idiosyncratic Components

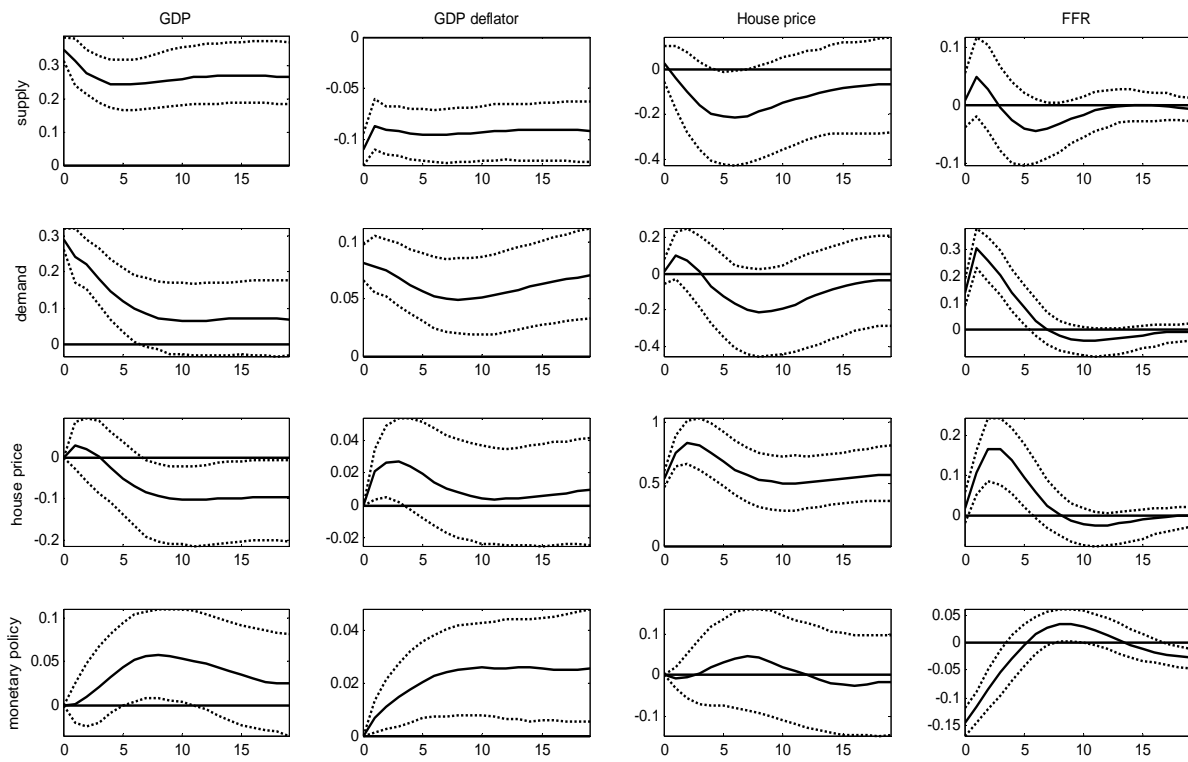
	Non-performing loans/total loans	Equity capital/ assets	Return on assets	Change in loans	Non-interest income/ net operating income
Common component	0.7	0.53	0.8	0.87	0.66
Idiosyncratic component	0.64	0.77	0.52	0.45	0.7

Table 1.6: Regression Results

Notes: The dependent variables are the impulse response functions for the non-performing loans ratio, non-interest income ratio and loans to expansionary monetary policy and house price shocks. Explanatory variables are demeaned bank characteristics as defined in Section 4.2.2 and the Appendix. A full set of state dummies is included. ***, **, * = significance at the 1%, 5%, 10%-level. Heteroscedasticity-robust standard errors are in brackets. NPL stands for the non-performing loans ratio, non-interest for the non-interest income ratio.

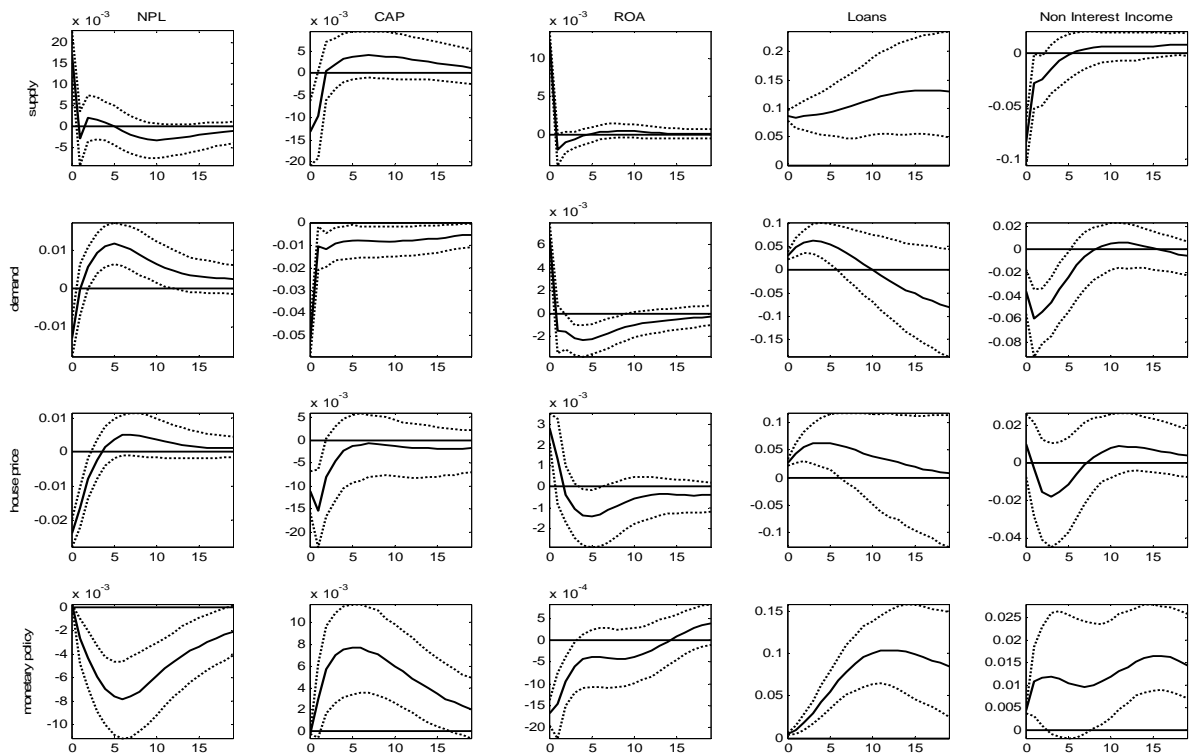
	Monetary policy shock						House price shock					
	Loans		Non-performing loans		Non-interest income		Loans		Non-performing loans		Non-interest income	
	$\frac{1}{2}$ year	1 year	$\frac{1}{2}$ year	1 year	$\frac{1}{2}$ year	1 year	$\frac{1}{2}$ year	1 year	$\frac{1}{2}$ year	1 year	$\frac{1}{2}$ year	1 year
Size	-0.524** -0.237	-0.693** -0.327	-0.004 -0.021	-0.004 -0.016	-0.193** -0.087	-0.189** -0.076	-2.047*** -0.567	-2.431*** -0.714	0.07 -0.081	0.074 -0.058	-0.039 -0.112	0.094 -0.141
Squared size	0.023** -0.01	0.030** -0.014	0.000 -0.001	0.000 -0.001	0.008** -0.004	0.008** -0.003	0.088*** -0.024	0.103*** -0.03	-0.003 -0.003	-0.003 -0.002	0.002 -0.005	-0.004 -0.006
Connectedness	-0.056 -0.531	0.035 -0.727	-0.003 -0.043	-0.019 -0.035	0.041 -0.144	-0.006 -0.106	-1.117 -1.193	-1.244 -1.352	0.027 -0.066	0.021 -0.049	-0.574** -0.281	-0.261 -0.255
Liquidity	-0.08 -0.106	-0.074 -0.149	0.007 -0.012	0.001 -0.01	-0.034 -0.03	-0.009 -0.021	0.3 -0.231	0.535** -0.27	-0.006 -0.016	-0.015 -0.012	0.170*** -0.048	0.173*** -0.044
Capitalization	0.199 -0.301	0.351 -0.415	0.025 -0.035	0.045 -0.027	-0.227** -0.089	-0.125** -0.062	-0.491 -0.777	-0.39 -0.895	0.055 -0.057	0.005 -0.039	0.403*** -0.155	0.467*** -0.135
Risk	-0.952 -0.99	-1.514 -1.377	0.047 -0.144	-0.086 -0.113	-0.545* -0.286	-0.434** -0.215	-0.713 -2.348	-0.251 -2.655	-0.962*** -0.244	-0.519*** -0.15	-0.01 -0.52	0.796* -0.445
Cons. loans/loans	-0.004 -0.115	-0.008 -0.162	-0.008 -0.011	0.001 -0.008	-0.031 -0.036	-0.008 -0.026	0.017 -0.249	-0.002 -0.287	0.042*** -0.016	0.020* -0.012	0.190*** -0.048	0.232*** -0.052
RE loans/loans	0.058 -0.071	0.046 -0.1	-0.014* -0.008	-0.007 -0.006	-0.059*** -0.02	-0.038** -0.015	0.443*** -0.163	0.472** -0.185	0.003 -0.012	0.024*** -0.008	0.033 -0.036	0.049 -0.033
Global bank	-0.036 -0.05	-0.072 -0.071	-0.005 -0.007	0.000 -0.005	0.026 -0.016	0.016 -0.013	-0.151 -0.154	-0.145 -0.171	0.01 -0.006	-0.005 -0.005	-0.017 -0.032	-0.059** -0.029
Constant	0.122*** -0.035	0.182*** -0.049	-0.008** -0.004	-0.009*** -0.003	0.012 -0.011	0.015* -0.008	0.130* -0.078	0.164* -0.093	-0.016*** -0.005	-0.001 -0.004	-0.057** -0.024	-0.019 -0.018
# of banks	1,471	1,471	1,471	1,471	1,471	1,471	1,471	1,471	1,471	1,471	1,471	1,471
R ²	0.096	0.101	0.073	0.09	0.074	0.063	0.074	0.069	0.096	0.078	0.107	0.127

Figure 1.1: Impulse Response Functions of Macroeconomic Factors



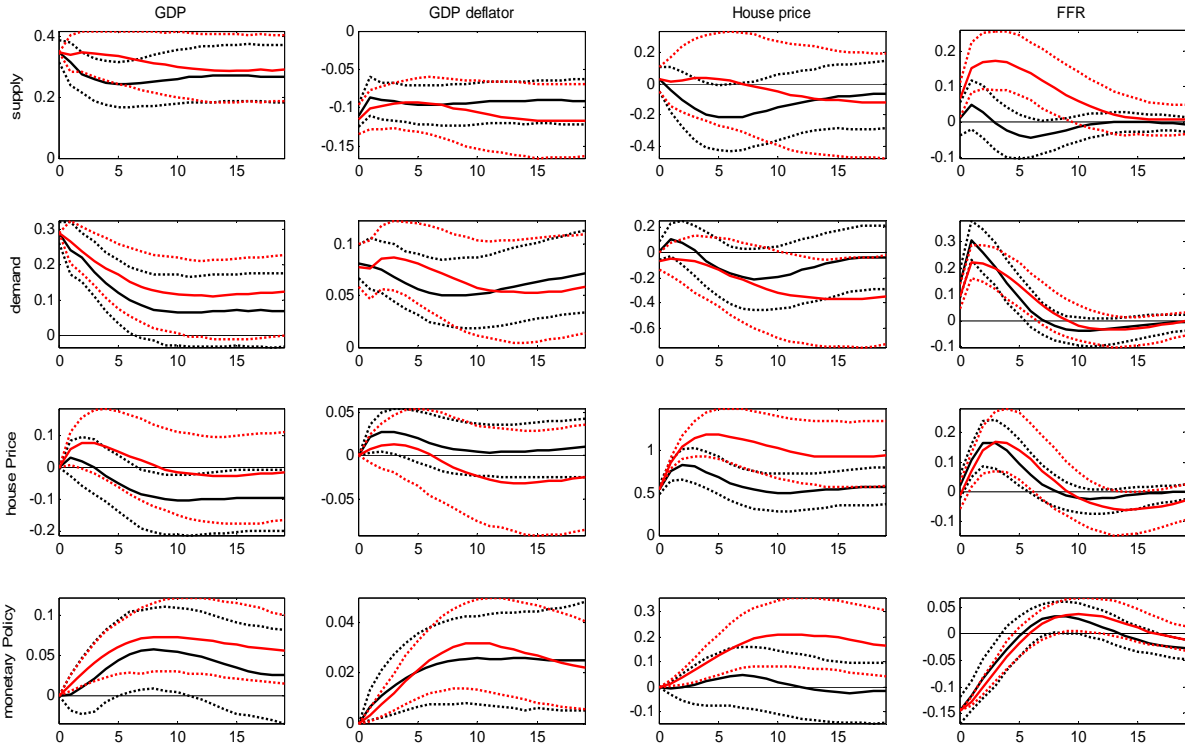
Notes: We show the median and the 90 percent confidence bands. In percent (GDP, the GDP deflator and house prices) and in percentage points (FFR = Federal Funds rate)

Figure 1.2: Impulse Response Functions of Median Banking Variables



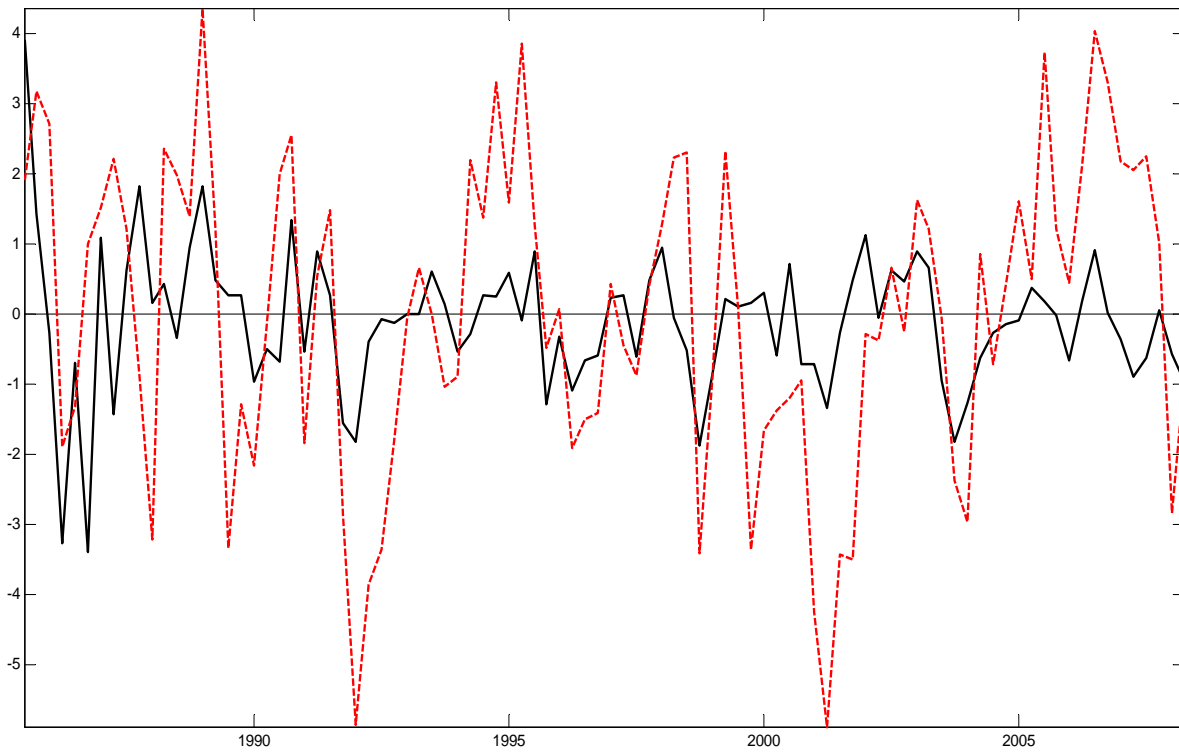
Notes: We show the median and 90 percent confidence bands. In percent (loans) and in percentage points (the ratios).

Figure 1.3: Impulse Response Functions of Macroeconomic Factors from the Baseline FAVAR and a VAR without Micro-Level Information



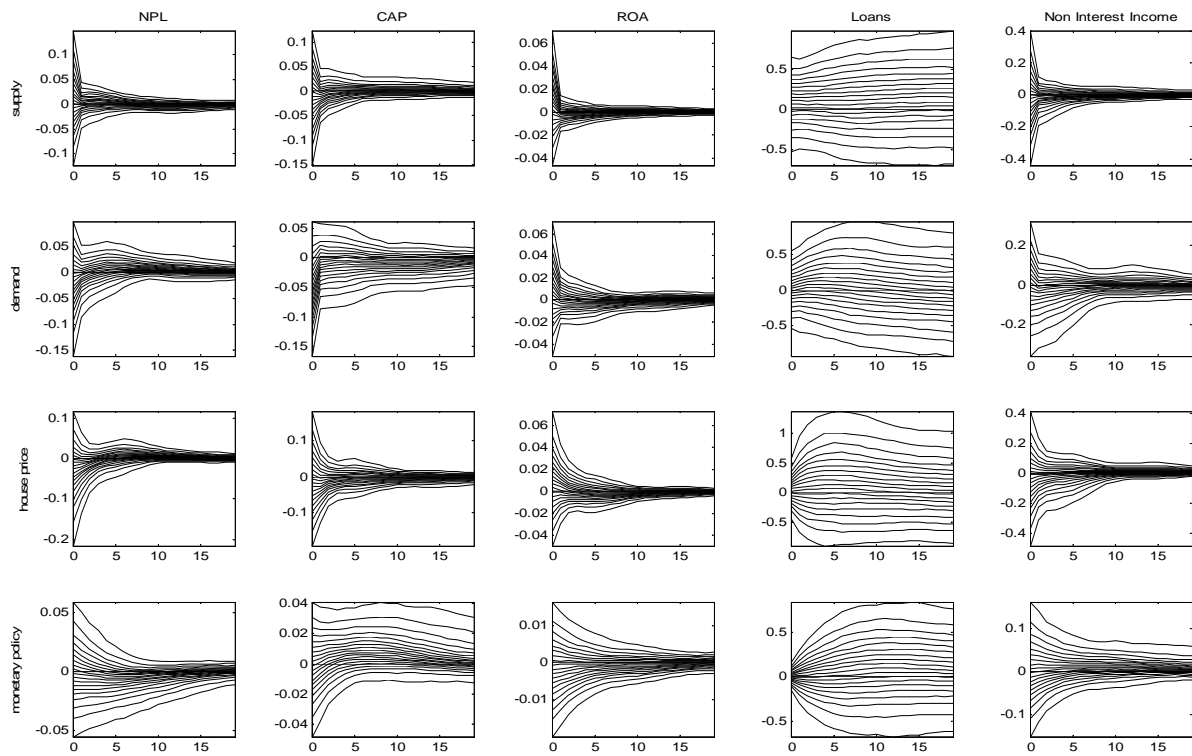
Notes: We show the median and 90 percent confidence bands of the benchmark FAVAR model (black) and a standard VAR with the five median banking variables (red). In percent (loans) and in percentage points (the ratios). The size of the shocks (i.e. the contemporaneous impact of supply and demand shocks on GDP, of house price shocks on house prices and of monetary policy shocks on the Federal Funds rate) obtained from the VAR was standardized to be the same as the size of the shocks obtained from the FAVAR.

Figure 1.4: Monetary Policy Shock Series



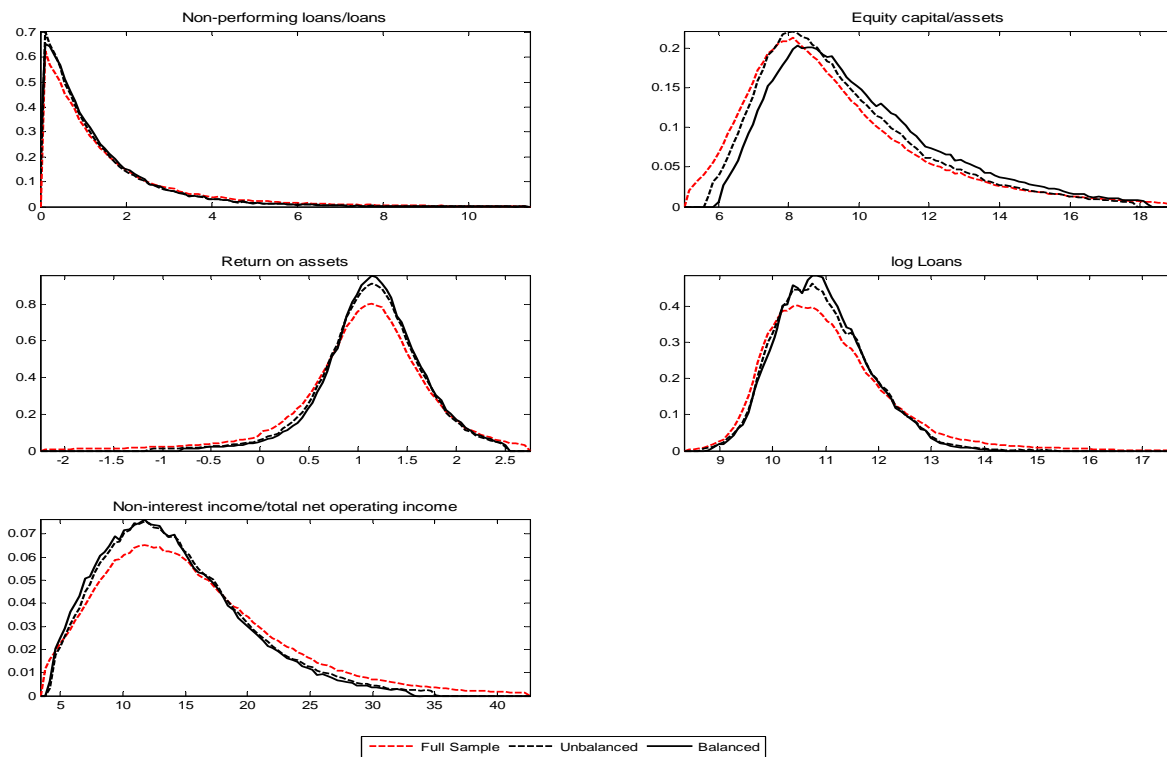
Notes: Shocks estimated based on the benchmark FAVAR, i.e. the model including bank-level information, (solid black) and the VAR with the median banking variables (dashed red). The size of the shocks is one standard deviation.

Figure 1.5: Impulse Response Functions of Individual Banks



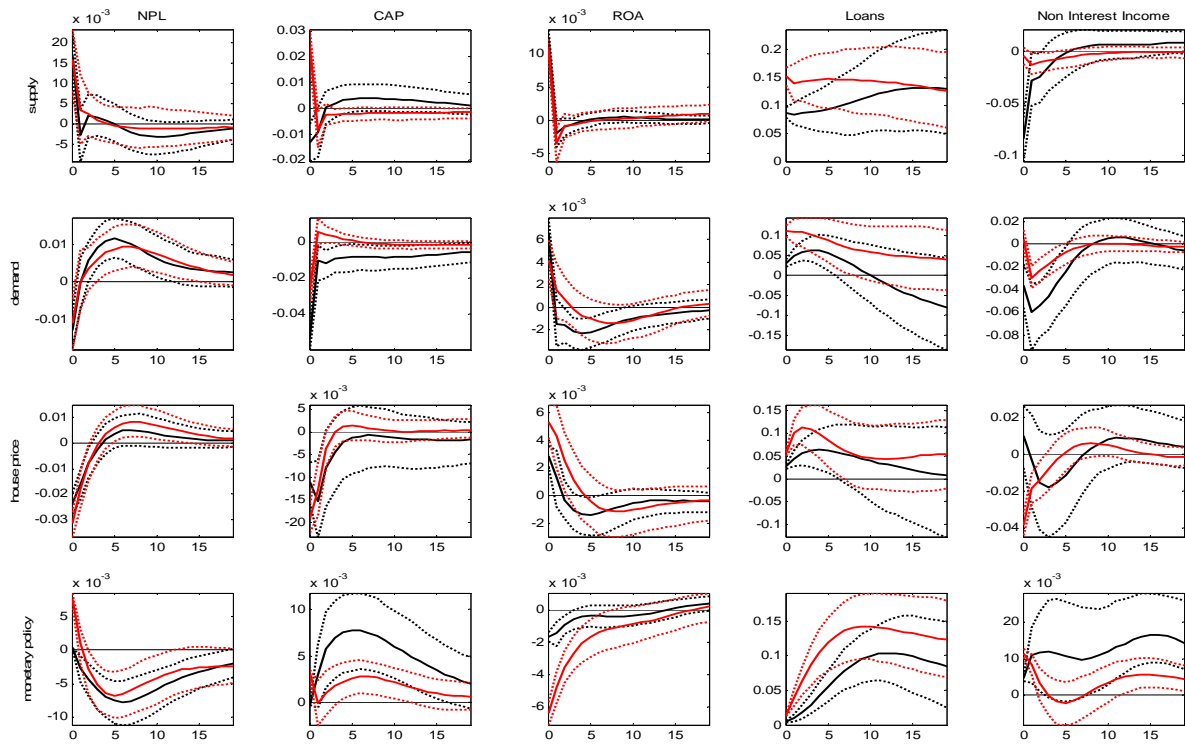
Notes: Point estimates of impulse response functions to one standard deviation shock. In percent (loans) and in percentage points (the ratios). We show the 5th to 95th quantiles instead of all impulse response functions for better visibility.

Figure 1.6: Kernel Densities of Banking Variables - Balanced versus Unbalanced Data



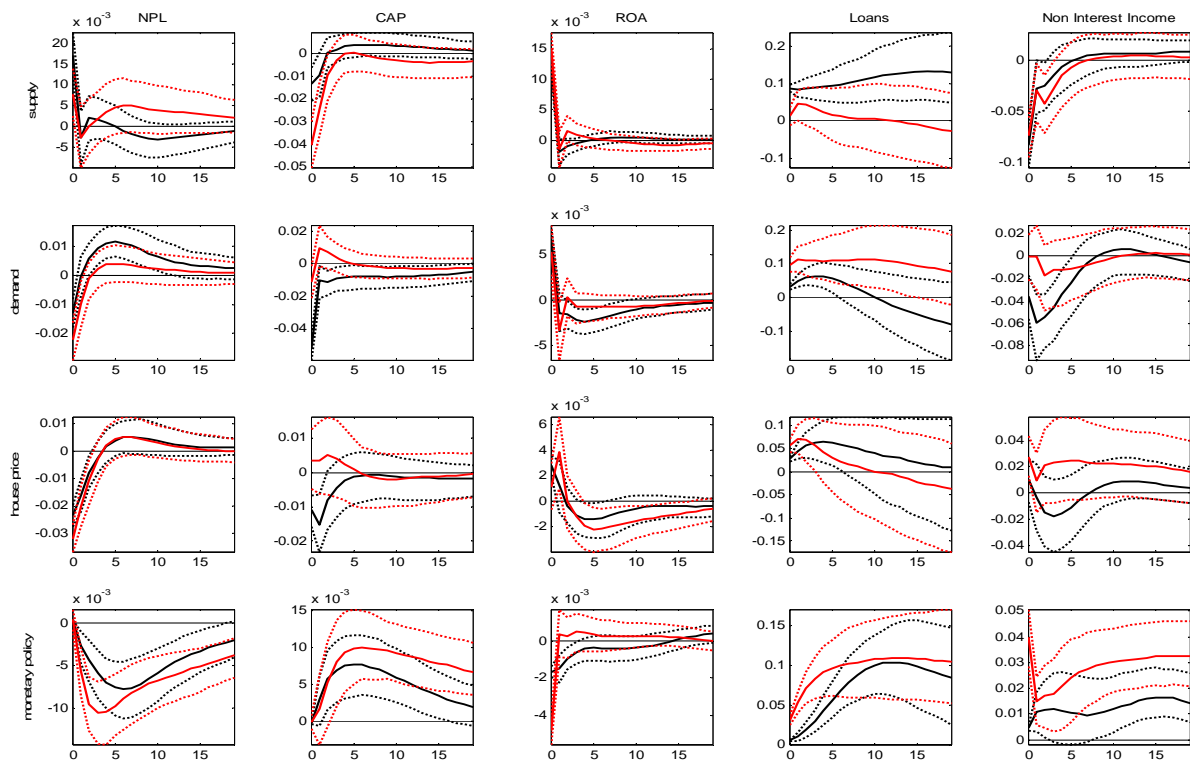
Notes: Dashed red, dashed black and solid black lines show kernel density estimates of full, unbalanced and balanced dataset respectively. The full sample is obtained after removing implausible values and outliers (11,466 banks). The balanced sample contains which operate over the entire sample period (1,471 banks). The unbalanced panel contains banks which operated at least 40 quarters (3,755 banks). The support used to estimate the kernel densities is given by the 1st and 99th percentile of the distribution of the full dataset.

Figure 1.7: Impulse Response Functions of Median Bank Variables from Baseline FAVAR and a FAVAR Estimated based on Unbalanced Panel of Banks



Notes: We show the median and 90 percent confidence bands. In percent (loans) and in percentage points (the ratios). Black: baseline model; Red: alternative model

Figure 1.8: Impulse Response Functions of Median Bank Variables from Baseline FAVAR and a FAVAR with Risk Factor Ordered below the Monetary Policy Rate



Notes: We show the median and 90 percent confidence bands. In percent (loans) and in percentage points (the ratios). Black: baseline model; Red: alternative model

1.9 Appendix to Chapter 1

Table 1.7: Definition of Bank Level Variables

Variable	Definition	Call Report Item
Consumer loans	Loans to individuals for households, family, and other personal expenditures	rcfd1975
Equity capital/assets (CAP)	Ratio of equity capital to total assets	rcfd3210 / rcfd2170
Interconnectedness	The share of federal funds purchased in total assets as a proxy for the exposure to the interbank market (King 2008). Interbank borrowing is measured through the average quarterly of federal funds purchased and securities sold under agreements to repurchase.	rcfd3353
International bank	We label a bank "international" if it is affiliated with a global bank holding company (Cetorelli and Goldberg 2012), and we construct a dummy variable which is 1 if a bank is international and 0 otherwise. This procedure results in 36 international active banks.	Global bank holding companies' foreign affiliates are identified through a positive entry in any of the Call Report entries due to foreign affiliates (rcon2941), due from foreign affiliates (rcon2163), total loans of foreign affiliates (rcfn2122) or C&I loans of foreign affiliates (rcfn1766) in one or more banks controlled by the bank holding company.
Liquidity	Liquidity is measured through the ratio of cash holdings and total securities relative to the balance sheet total.	Prior to 1994Q1: sum of the Call Report entries rcfd0390 (total investment securities – book value), rcfd2146 (total assets held in trading accounts) and rcfd1350 (federal funds sold and securities purchased under agreements to resell). After 1994Q1: sum of the Call Report entry lines rcfd1754 (held to maturity securities, total) rcfd1773 (available for sale securities, total) rcfd3545 (trading assets, total) and rcfd1350 (federal funds sold and securities purchased under agreements to resell).
Non-interest income/net operating income	Share of non-interest income in net operating income. Net operating income is defined as total interest and non-interest income less interest expenses.	Non-interest income (riad4079); Total interest and non-interest income (riad4000); Interest expenses (riad4073)
Non-performing loans/total loans (NPL)	Share of total non-performing loans in total loans.	Sum of Call Report item rcfd1403 (total loans and lease finance receivables: nonaccrual) and Call Report item rcfd1407 (total loans and lease finance receivables: past due 90 days or more and still accruing).
Real estate loans	Loans secured by real estate	rcfd1410
Return on assets (ROA)	Ratio of net income to total assets	riad4340/rcfd2170
Size	Log of banks' real gross total assets, i.e. assets divided by the GDP deflator.	rcfd2170

Identification of Shocks

Suppose that \hat{u}_t is the $r + M$ vector of reduced-form VAR residuals where the latent and observable factors are the endogenous variables. The $(r + M) \times 1$ vector of (orthogonalized) Cholesky residuals v_t is estimated as

$$\hat{v}_t = \hat{A}\hat{u}_t$$

where \hat{A} is the lower triangular Cholesky matrix of $\text{cov}(u_t)$. We partition \hat{v}_t in two parts, the 2×1 vector of Cholesky residuals associated with GDP growth and GDP deflator inflation $\hat{v}_t^{1\dots 2}$ and the $(r + M - 2) \times 1$ vector of Cholesky residuals associated with house price inflation, the Federal Funds rate and the latent banking factors $\hat{v}_t^{3\dots r+M}$, and $\hat{v}_t = [\hat{v}_t^{1\dots 2'} \hat{v}_t^{3\dots r+M'}]'$. The estimated vector of structural shocks \hat{w}_t is related to \hat{v}_t as follows. Let $\hat{w}_t^{1\dots 2} = R\hat{v}_t^{1\dots 2}$ and $\hat{w}_t^{3\dots r+M} = \hat{v}_t^{3\dots r+M}$ where R is the rotation matrix and $R'R = I_2$ and, by construction, $\text{cov}(\hat{w}_t) = I_{r+M}$.

The rotation matrix R is chosen such that the identifying restrictions specified in the main text are satisfied. We follow Rubio-Ramírez, Waggoner and Zha (2010) and let Ω be an 2×2 random matrix with each element having an independent standard normal distribution and $\Omega = QR$ be the QR decomposition of Ω .

It turns out that more than one R satisfies the sign restrictions. We draw until we retain K rotation matrices which satisfy all restrictions. Following Fry and Pagan (2007) we choose out of K R s that satisfy the sign restrictions, the R that leads to impulse response functions which are as close as possible to their median values; for details see Fry and Pagan (2007). K is set at 100 to keep it computationally tractable.

Chapter 2

In Search for Yield? Survey Based Evidence on Bank Risk-Taking

2.1 Motivation

Monetary policy decisions might affect risk taking of banks (Borio and Zhu 2012, Rajan 2005)¹. A reduction in the policy rate reduces returns especially on low risk investments. To keep the average return on assets constant, bank managers have incentives to shift into riskier credit market segments. Expansionary monetary policy might thus induce a "search for yield" by banks and impair financial stability.

We use a factor-augmented vector autoregressive model (FAVAR) for the US to analyze the reaction of banks to monetary policy shocks. Our empirical model comprises GDP growth, GDP deflator inflation, the monetary policy interest rate, and banking

This chapter is based on joint work with Claudia Buch and Sandra Eickmeier entitled "In search for yield? Survey based evidence on bank risk-taking" which is forthcoming in the *Journal of Economic Dynamics and Control*.

¹The link between low policy rates, risk taking, and "search for yield" has been described as follows: "[...] These behaviors can be compounded in an environment of low interest rates. Some investment managers have fixed rate obligations which force them to take on more risk as rates fall. Others like hedge funds have compensation structures that offer them a fraction of the returns generated, and in an atmosphere of low returns, the desire to goose them up increases. Thus not only do the incentives of some participants to "search for yield" increase in a low rate environment, but also asset prices can spiral upwards, creating the conditions for a sharp and messy realignment." (Raghuram G. Rajan, The Greenspan Era: Lessons for the Future, Saturday, August 27, 2005, Jackson Hole, Wyoming).

factors. The banking factors summarize information on business lending provided in the Federal Reserve’s *Survey of Terms of Business Lending* (STBL). The STBL questionnaire asks banks to rate the risk of new loans based on a borrower’s credit history, cash flow, credit rating, access to alternative sources of finance, management quality, collateral, and quality of the guarantor. This information is used to classify loans into different risk categories ex ante. Shifts across categories thus reflect changes in bank risk taking. The survey also distinguishes small domestic, large domestic, and foreign banks.

We identify risk-taking effects following monetary policy shocks by exploiting heterogeneity across different banks and loan market segments. We distinguish responses of new loans and loan spreads across different types of banks and different loan risk categories. Our results suggest that, on average over the sample period, small domestic banks significantly increase new loans to high risk borrowers after expansionary monetary policy shocks. The composition of loan supply of small banks shifts towards riskier loans. Large domestic banks give out more new high risk loans, but the composition of their loan portfolio does not change significantly. Foreign banks increase risk only during the mid-2000s, when interest rates were particularly low for a prolonged period of time (‘too-low-for-too-long’). Changes in the risk composition of loan portfolios are not compensated by higher risk premia. Banks rather shift their (new) loan portfolios towards higher risk loans and charge a lower risk premium. This is how the risk-taking channel is defined in Borio and Zhu (2012): banks are willing to take on more risk, and this is not compensated by an increase in the risk premium.

Our empirical research is motivated by theoretical work modeling the link between low policy interest rates and risks in banking. This research shows that, in the presence of asymmetries in information and agency problems, bank-specific features affect bank risk taking. Risk may increase as a consequence of additional availability of liquidity which lowers the risk aversion of banks (Diamond and Rajan 2009, Acharya and Naqvi 2012), because value-at-risk constraints are weakened (Adrian and Song Shin 2010), or because adverse selection problems in the credit market are mitigated, thereby reducing banks’ screening incentives (Dell’Ariccia and Marquez 2006, Dell’Ariccia, Laeven, and Marquez 2014). From a theoretical point of view, lower policy rates should thus increase new loans to riskier borrowers. Moreover, banks which are prone to agency problems are affected more.

Our data allow modeling heterogeneity across banks and loan categories. In addition, our paper contains five features which we consider crucial for the identification of risk-

taking effects. First, the STBL provides information on new loans, not on outstanding loans. We can thus take account of the fact that the risk-taking channel as advanced by Borio and Zhu (2012) and Rajan (2005) describes the incentives to engage in ex ante riskier projects. Most previous studies do not distinguish between realized risk (on existing loans) and new risk (on new loans). Exceptions are the panel regressions by Ioannidou, Ongena, and Peydro (2009) and Jimenez, Ongena, Peydro, and Saurina (forth.), who use (confidential) credit register data at the bank-borrower level. These studies tend to find evidence in favor of the risk-taking channel of monetary policy.

Second, the STBL provides information on volumes and prices of new loans by type of risk. This allows assessing whether loan supply or loan demand effects dominate in the transmission of monetary policy shocks: if loan volumes and lending rates increase, demand effects dominate; if loan volumes increase and lending rates fall, supply effects are more important. Ignoring systematic changes in the quality of borrowers following monetary policy shocks would flaw any separation of supply and demand effects. Our data allow "holding constant" the quality of borrowers.

Third, our data contain information on how banks perceive the risk of new loans. We consider this to be a crucial ingredient to cleanly identify the effects of monetary policy shocks on the attitudes of banks towards risk taking. Studies like Ioannidou, Ongena, and Peydro (2009) or Jimenez, Ongena, Peydro, and Saurina (forth.) work under the implicit assumption that the ex post risk of borrowers, or observable risk characteristics of borrowers, are fully aligned with ex ante risk perceptions of banks. Our data allows us to side step such assumptions using information on ex ante risk taking from the point of view of the bank manager.

Fourth, the FAVAR model includes a large amount of information on banks and thus allows modeling mutual feedback between the banking sector and the macroeconomy. Previous papers using panel models allow modeling bank heterogeneity, but they are more restrictive in terms of the modeling of macroeconomic shocks (Altunbas, Gambacorta, and Marques-Ibanez 2012, Ioannidou, Ongena, and Peydro 2009, Jimenez, Ongena, Peydro, and Saurina forth.). By contrast, work using time series (VAR or FAVAR) models which do not exploit highly disaggregated banking information (Angeloni, Faia, and Duca 2010, Eickmeier and Hofmann 2013, or Lang and Nakamura 1995) or univariate regressions (Nicolo, Dell'Ariccia, , Laeven, and Valencia 2010) cannot assess heterogeneity or at least not to the same degree.

Fifth, like other multivariate time series analyses, the FAVAR model captures interactions between macroeconomic factors and the banking system and looks at the impact of identified, mutually orthogonal, macroeconomic shocks. By contrast, panel studies typically regress risk measures on monetary policy interest rates and additional explanatory variables. These studies allow interest rates and other macroeconomic factors to affect banks, but they do not take into account feedback from banks to the macroeconomy. Yet, macroeconomic indicators are reduced-form constructs and a convolution of different types of shocks. The transmission may be different for different types of shocks, which we can account for. We also account for the fact that policy interest rates might have been "too low for too long" by allowing parameters to change across different regimes.

In Section 2.2, we describe our data. In Section 2.3, we explain the FAVAR methodology. In Section 2.4 we present and discuss our empirical results. In Section 2.5, we conclude.

2.2 Data

2.2.1 Macroeconomic Data

Our set of macroeconomic variables is largely in line with typical small-scale macroeconomic VARs. The data comprise differences of the logarithms of GDP, of the GDP deflator, and the level of the effective Federal Funds rate. Data on the Federal Funds rate are retrieved from freelunch.com, a free Internet service provided by Moody's Economy.com. Data on GDP and the GDP deflator are taken from the Bureau of Economic Analysis. The macroeconomic series from 1997Q2 to 2008Q2 are plotted in Figure 2.1(a).

To check the robustness of our results, we include, alternatively, real residential property price inflation, real commercial property price inflation, and real private fixed investment as additional control variables in our baseline model. One could argue that these variables capture collateral which has been shown to be an important determinant of bank lending (Guerrieri and Iacoviello 2012). Our main results are not materially affected. The reason might be that collateral is already sufficiently covered in our large dataset as we will explain in the next subsection. We therefore proceed in what follows with three macroeconomic variables.

2.2.2 Banking Data

Our source for banking data is the Federal Reserve's quarterly *Survey of Terms of Business Lending* (STBL)². This survey collects data on gross new loans (in US dollars) made during the first full business week in the mid-month of each quarter. Our sample period is 1997Q2 to 2008Q2. The beginning of the sample is restricted by the availability of the information on loan risk, which starts with the May 1997 survey. We exclude the period after the second quarter of 2008 because unconventional monetary policy measures weaken the usefulness of the Federal Funds rate to identify monetary policy shocks. We check robustness with respect to the end date of the sample period and stop before the onset of the financial crisis in 2006Q4. Our main results (available upon request) are unaffected.

The panel for the survey is a stratified sample of more than 400 banks. The STBL contains information on loan volumes and on loan contract terms. This information is available for all commercial banks and for three banking groups: large domestic banks, small domestic banks, and US branches and agencies of foreign banks. The data do not distinguish between large and small foreign banks. However, it is well known that internationally active firms and banks are larger than their domestic counterparts (Cetorelli and Goldberg 2012).

In Figure 2.2 we plot new loans from the STBL alongside a comparable new loan series compiled from the DealScan database on loan origination.³ We also compare the evolution of those two new loan series with the change of total (outstanding) commercial and industrial loans on the balance sheet of the US banking sector from the Federal Reserve Statistical Release Assets and Liabilities of Commercial Banks in the United States - H8.⁴ Over the last decade both series on new loans track the large swings, especially the decline starting in 2000 and the subsequent increase, in changes in aggregate bank

²See Brady, English, and Nelson (1998) for a detailed discussion of the structure of the STBL. We choose not to combine the STBL data with information from other sources on US banks such as the Call Reports. We do not know the identities of the banks responding to the STBL survey, and we want to avoid introducing additional measurement or aggregation errors.

³We are grateful to Victoria Ivashina for kindly sharing the aggregate new loan data from the DealScan Database (starting in 2000) with us. The DealScan data is provided by Reuters and covers large bank loans. These loans are mostly originated by a group of two or more banks. See Ivashina and Scharfstein (2010) for a detailed discussion of this data and differences to aggregate bank credit data.

⁴All three credit series are seasonally adjusted and expressed in real term. The series are indexed to 1 in 2000Q1.

credit reasonably well. However, each of the databases has a different coverage⁵, which limits direct comparability of the data and explains differences in the series.⁶

2.2.3 Measuring Loan Risk

The STBL provides information on the riskiness of new loans. Banks are asked to classify new business loans extended during the survey week into one of the following four categories of increasing risk: "minimal risk" loans (which account for a share of 8% on average over the sample for all banks), "low risk" (23%), "moderate risk" (41%), and "acceptable risk" (28%). "Minimal risk" loans are virtually safe loans.⁷ Note that "acceptable risk" is somewhat of an euphemism since it reflects the highest risk category. In order to stick to the original labeling, we use these terms throughout the paper. The classification of loans is based on a large number of indicators, which are condensed into a risk rating. The classification takes into account hard information (cash flow, credit history, credit ratings, quality of collateral) as well as soft information (management quality).

Our identification of risk taking is based on different responses across loan risk categories. If a worsening of one aspect of loan quality is fully compensated by an improvement along another dimension, the overall classification of the loan would not change. A shift in the composition of bank loans across different risk categories thus reflects changes in the overall credit standards for new loans. When presenting our results, we focus on differences in adjustment between loans which are categorized as most risky

⁵DealScan data covers mostly large, syndicated loans to large borrowers. In contrast, the STBL contains estimates of all new loans issued by the banking system. Moreover, the differences between the new loan series (from DealScan and the STBL) and bank credit emerge because changes in the volume of outstanding credit are not only the result of new loan origination, but also because of early repayment of existing debt by borrowers and the termination of nonperforming loans (see Bassett, Gilchrist, Weinbach, and Zakrajsek 2011 for a thorough discussion of this issue).

⁶While the STBL shows a rather strong reduction in new bank lending over 2000-2004, new lending from the DealScan database declines more moderately. Given that the DealScan data contain new loan origination to large borrowers only, this suggests that the reduction in bank lending during this period is largely attributable to reduced lending to smaller borrowers. We also observe that the increase in new lending over the 2004-2008 period is much more pronounced in the DealScan data than in the STBL data, indicating that lending to larger borrowers contributed most to the increase in total bank credit on the balance sheet. Finally, at the end of the sample we observe a large drop in new loans from the DealScan database, which is not visible in the STBL or the aggregate credit data. This is due to credit line drawdowns, which the STBL data contain but not the DealScan data (Ivashina and Scharfstein 2010).

⁷The survey defines the "minimal risk" category as follows: "Loans in this category have virtually no chance of resulting in a loss." See Data Appendix.

(“acceptable risk” loans) and as safe (“minimal risk” loans). Our main messages are, however, not much changed when we compare low and moderate risk with safe loans.

In Table 2.1, we show descriptive statistics on loan growth and loan spreads. Over the full time period, there has been a contraction in new loans across all loan categories with the contraction being strongest in the minimal risk category. The patterns differ across the types of banks though: the shift from low to high risk lending has been strongest for the foreign banks. Small domestic banks, in contrast, have increased low risk loans, while the adjustment for the large domestic banks has been fairly balanced. If anything, these patterns in the data would suggest that small banks have become safer while larger banks have become more risky. To what extent these adjustments reflect the response to expansionary monetary policy is an issue which we address below. Loan spreads are increasing in loan risk, as expected. They are higher for the small than for the large domestic and the foreign banks.

Figures 2.3(a) and 2.3(b) show the evolution of the share of “acceptable” (high) risk loans in total loans and the interest rate spread charged on high risk loans (black lines) together with the Federal Funds rate (blue dotted lines). It is apparent that high risk lending was particularly elevated and that risk spreads were particularly low when the Federal Funds rate was at low levels in the mid-2000s. While the share of high risk lending by foreign banks reached its peak around 2003, small and large domestic banks were most risky around 2005. In Section 2.4.5, we will test whether risk taking is specific to the period 2003-2005.

When interpreting our results, it should be borne in mind that we focus on (new) business loans and on risk perceptions of bank managers. This has four implications for the interpretation of our results.

First, we have no information on real estate or consumer loans. This limits the general applicability of our results. At the same time, it may be advantageous to focus on a loan market segment that has not been much under the influence of government policies to promote risk taking, unlike in the subprime residential mortgages loan segment. Calomiris (2009) provides an overview of government measures encouraging risk taking in the mortgage market.

Second, off-balance sheet activities and other credit substitutes are not covered. These activities might be particularly important for foreign and large banks.

Third, we have information about banks' lending decisions based on their current perceptions about future loan performance. But we do not know the extent to which this perception is matched by the performance of loans ex post.

Finally, we will show below that loan supply effects dominate loan demand effects after monetary policy shocks for small banks. Yet, we cannot fully exclude that the composition of loan demand might shift as well, i.e. that more or less risky borrowers demand loans after the shocks.

2.2.4 Additional Information on Loan Terms

In response to macroeconomic shocks, banks can adjust both, loan volumes and interest rates. Therefore, our analysis is not based only on loan volumes but also on loan spreads. Loan spreads are measured as difference between the risky lending rate and the corresponding riskless rate. We use the one-year Treasury bill rate because this maturity corresponds roughly to the average maturity of business loans in the STBL.

The STBL additionally contains information on the shares of loans made under commitment, secured by collateral, subject to prepayment penalty, on loan size, and on loan maturity. Including these variables when estimating banking factors minimizes omitted variables problems. Moreover, collateralization and loan maturity may not just represent control variables but also choice variables, which contain information on risk taking by banks.

2.2.5 Data Transformation

We include the banking variables for the entire banking sector, for the subgroups of banks, and for the four different risk categories. We divide loan volumes by the GDP deflator. Hence, loans enter in real terms. Moreover, we subtract from the risky lending rate the corresponding riskless rate of the same maturity, i.e. the 1-year Treasury bill rate, and we include this spread in the empirical model. We use the 1-year Treasury bill rate since one year roughly corresponds to the average maturity of business loans in the STBL over our sample. Our panel of banking data thus contains 140 variables.⁸

We treat the banking data as usual for factor analysis. All series are seasonally adjusted. Stationarity of the 20 loan series in the dataset is ensured by taking differences of

⁸Two of the 140 series have missing values in one quarter each. We use the EM algorithm to interpolate these series. See for details Stock and Watson (2002)

their logarithms. The time series on loan rates, the percentage share of loans made under commitment, and the percentage share of loans secured by collateral can be considered to be stationary in levels. Hence, we do not (log) difference them. The stationary series are then demeaned and standardized to have unit variance.

Finally, we remove outliers, which are defined as observations with absolute median deviations larger than three times the interquartile range. These are replaced by the median value of the preceding five observations (Stock and Watson 2005). All series from the survey are then summarized in a $N(= 140) \times 1$ vector $X_t = [x_{1t} \dots x_{Nt}]'$, and X_t enters the FAVAR model.

2.3 Methodology

Our empirical FAVAR model integrates the banking and the macroeconomic data in a consistent framework. The model combines advantages of bank-level panel studies, which allow exploiting a large set of information on bank heterogeneity, with advantages of macroeconomic VAR models, which allow modeling the dynamic interaction between different variables.

2.3.1 The FAVAR Model

We assume that our vector of banking variables collected from the STBL (X_t) follows an approximate dynamic factor model (Stock and Watson 2002, Bai and Ng 2002) where each series x_{jt} is driven by the $r \times 1$ vector of common factors F_t and an idiosyncratic (series-specific) component e_{jt} :⁹

$$x_{jt} = \lambda_j' F_t + e_{jt} \tag{2.3.1}$$

where λ_j is a $r \times 1$ vector of factor loadings. The number of common factors is typically much smaller than the number of variables in X_t , hence $r \ll N$. Common and series-specific components are orthogonal, the common factors are mutually orthogonal; idiosyncratic components can be weakly mutually and serially correlated in the sense of Chamberlain and Rothschild (1983).

⁹For a more thorough discussion of the empirical framework, see Bernanke, Boivin, and Eliasziw (2005) and Buch et al. (forth.).

F_t can be decomposed into two parts: a set of observable factors G_t and a set of latent (or unobservable) factors H_t which both drive X_t : $F_t = [G_t' H_t']'$. We assume that G_t comprises the differences of the logarithms of GDP (Δy_t) and of the GDP deflator (Δp_t) as well as the level of the effective Federal Funds rate (ffr_t). The unobserved "banking" factors (H_t) need to be estimated. They summarize the banking variables and are orthogonal to the observable macroeconomic factors. Banking factors are thus included in the policy reaction function. The factors are assumed to follow a $VAR(p)$ model:

$$\begin{pmatrix} \Delta y_t \\ \Delta p_t \\ H_t \\ ffr_t \end{pmatrix} = z + \Theta(L) \begin{pmatrix} \Delta y_{t-1} \\ \Delta p_{t-1} \\ H_{t-1} \\ ffr_{t-1} \end{pmatrix} + v_t \quad (2.3.2)$$

where z comprises constants, $\Theta(L)$ is a lag polynomial of finite order p , and v_t is an error term which is *i.i.d.* with zero mean and covariance matrix Q .

2.3.2 Shock Identification

We identify monetary policy shocks recursively. We carry out a Cholesky decomposition of the covariance of v_t and we order the Federal Funds rate last. The orthogonal residuals associated with the equation explaining the Federal Funds rate are interpreted as monetary policy shocks.

Our identification scheme for the monetary policy shocks implies that GDP, aggregate prices and the latent banking factors do not react contemporaneously to monetary policy shocks. By contrast, the monetary policy instrument can respond instantaneously to all macroeconomic shocks. These are standard assumptions in the SVAR literature (Iacoviello 2005, Jarocinski and Smets 2008).

A crucial part of our analysis is the ordering of banking and macroeconomic factors. By ordering the policy instrument below the factors summarizing the banking variables, we follow most of the SVAR literature which jointly models macroeconomic and credit variables (Ciccarelli, Maddaloni, and Peydro 2010). The identification scheme implies that monetary policy can react instantaneously to banking shocks, but not vice versa. The STBL is collected in order to inform the Federal Reserve's monetary policy decisions. Insofar, the information in the survey should be part of the information set of the Fed, which supports our identification assumption.

It is somewhat more questionable whether banks react with a lag to unexpected movements in the policy rate. Berrospide and Edge (2010), for instance, assume that banking variables can react contemporaneously to innovations in the Federal Funds rate. Yet, there are good reasons to believe that banks adjust sluggishly to monetary policy: existing contracts need to be renegotiated; banks do not want to interrupt close customer relationships; lending rates of banks are sticky and do not react quickly to market interest rates (Berger and Hannan 1991). This supports our choice to order banking factors before the Federal Funds rate. We also note that we restrict, in our baseline model, banking factors not to react instantaneously to movements in the monetary policy rate. However, individual banking variables included in the large banking dataset can still respond immediately to policy shocks. Nevertheless, we re-estimate the model with the ordering of the banking factors and the policy rate reversed. Our main results remain the same. How to best identify banking shocks or financial shocks more generally in a time series context and how to disentangle them from monetary policy shocks remains an unresolved issue, and further work on this issue is certainly needed.

2.3.3 Estimation and Specification

The model is estimated in four steps. First, we regress each of the banking series x_{it} on G_t . Second, we estimate the "banking factors" H_t as the first $m = r - 3$ principal components (PCs) from the residuals, following Boivin and Ng (2006). Those are shown in Figure 2.1(c). Third, we model the joint dynamics of G_t and the estimate of H_t in a VAR model which we estimate equation-wise with OLS. Fourth, we identify monetary policy shocks as described above.

The first two estimation steps allow removing the observables from the space spanned by the latent factors and to estimate, later on, a more sparsely parameterized VAR model on our relatively short sample. To formally assess how useful the regression step is, we apply the information criterion IC_{p1} suggested by Bai and Ng (2002), which has been shown to perform well in small samples, to determine the number of common factors driving the raw dataset and the dataset after removal of the observables. The IC_{p1} suggests that 5 factors drive the raw dataset whereas only $m = 3$ factors are needed to explain the set of residuals obtained in the first step. This indicates that the observables lie in the factor space spanned by the raw (or unpurged) PCs (shown in Figure 2.1(b)) and that we may want to take this into account.

From Table 2.2 it is indeed apparent that the unpurged PCs tend to be highly correlated with the observables. The first factor is correlated with all three observables, the second and fourth factors are mainly correlated with the Federal Funds rate, the third factor with growth and inflation, while the last factor is only marginally correlated with the observables. Because the individual factors are not identified, we also compute the R^2 from a regression of each of the 3 observables on the set of 5 unpurged PCs and find that they are high: 0.35 for GDP growth, 0.45 for inflation and 0.73 for the Federal Funds rate. Hence, overall, the regression step allows us to include only 6 instead of 8 (observable and latent) factors in the VAR.

We nevertheless, as a check, re-estimate the model without the regression step, and included 5 unpurged PCs together with the 3 observables in the VAR. Results (available upon request) are very similar, but confidence bands tend to be slightly wider. This supports our strategy of estimating a VAR which is as sparsely parameterized as possible.

Beside the number of factors, the lag order p needs to be selected. We set it to 1, as suggested by the BIC. We experiment with a larger number of factors and with a lag order of $p = 2$, but results remain basically unaffected. Given the short sample, we adopt the sparser parametrization.

2.3.4 Commonality Among the Banking Variables

Factor models can be reliably estimated only if there is a reasonably high degree of comovement between the individual (banking) series. Table 2.3 shows the variance share on average over all variables in the large banking dataset explained by the first 6 unpurged PCs and by the 6 (observable and latent, i.e. purged) factors. The first 5 unpurged PCs explain 48% of the overall variation in the banking dataset, and the share is similar for the 3 observed and 3 latent purged PCs. This degree of comovement is not much smaller than shares of 60% or more usually found in macroeconomic datasets for the US (e.g. Boivin, Giannoni, and Mihov 2009, Eickmeier and Hofmann 2013). This high number is comforting given that, in survey data, reporting errors add to measurement error inherent in any dataset. The STBL data are based on the reported answers of the surveyed banks. The Federal Reserves' staff then generates estimates for the entire banking sector, which adds an additional estimation error.

Table 2.4 shows variance shares for loan growth and interest rate spreads explained by all (latent banking and observed macroeconomic) factors. The factors explain 27% of the variation in the growth of loans. Commonality tends to be higher for large than

for small banks. One explanation is that local conditions unrelated to macroeconomic developments play a more important role for smaller banks. Alternatively, this result could reflect that shocks underlying H_t first hit large (systemically relevant) banks and are then transmitted to the macroeconomy and/or to other banks in the system. For loan spreads, commonality is, with an average of 88%, much higher than for loan volumes. Commonality is again (slightly) lower for small than for large banks.

2.4 Empirical Results

With the data and empirical methodology at hand, we are now in the position to answer the question how monetary policy shocks affect bank behaviour. For each shock, we first look at the adjustment of loan volumes and loan spreads. In a second step, we investigate the adjustment across loan risk categories in order to analyze the effects of monetary policy shocks on bank risk taking.

2.4.1 Reaction of Macroeconomic Variables

We begin with an analysis of the macroeconomic adjustment processes. Figure 2.4 presents impulse responses of the macroeconomic variables to one standard deviation monetary policy shocks. The black lines represent the median impulse responses while the dark (light) blue shaded areas correspond to the confidence bands at the 68 (90)% significance level. These are constructed based on the bootstrap-after-bootstrap method proposed by Kilian (1998) which is based on 500 draws.¹⁰

Following an expansionary monetary policy shock, the adjustment of macroeconomic indicators is roughly in line with expectations. The Federal Funds rate drops on impact by about 20 basis points before gradually returning to zero after one year. The (marginally significant) increase in GDP is temporary, consistent with long-run real neutrality of monetary policy. The GDP deflator rises persistently, with a maximum effect reached after about two years.

¹⁰Following Bernanke et al. (2005), we do not take into account the uncertainty involved with the factor estimation, given that our cross section is very large.

2.4.2 Effects of Monetary Policy Shocks on Bank Lending and Loan Spreads

Before looking at changes in the composition of new bank loans, we study the response of total new banks loans (Figure 2.5(a)) and the interest rates charged (Figure 2.5(b)) to monetary policy shocks. Row 1 shows responses for all banks; Rows 2-4 show results for the banking groups. In the first column of each figure, we show the response of total new loans (of the entire banking system and the individual banking groups); Columns 2-5 present the responses across risk categories. Table 2.5 shows results of tests whether differences in the reactions between loans to high risk and to minimal-risk borrowers within the same banking group (Table 2.5(a)) and differences across banking groups (Table 2.5(b)) are significant. Numbers in bold indicate significance at the 90% level. We show the impact effects and the responses after one year. The impact effects reflect direct effects while those after one year include effects of movements in other (macroeconomic) variables induced by the original shocks.

Total new loans of the entire banking system increase by about 2% following a one standard deviation expansionary monetary policy shock (Figure 2.5(a)). The response of new loans is sluggish: the maximum effect is reached after almost two years. The response is also quite persistent.

The adjustment across banks differs. New loans of large domestic banks and of foreign banks do not react significantly to monetary policy shocks (Column 1, Rows 2-4). Small domestic banks, by contrast, contemporaneously and significantly increase new loans following the expansionary monetary policy shock. At the same time, average lending spreads on all new business loans drop (although the impact for small banks is barely significant) (Figure 2.5(b)).¹¹ Hence, for the group of small banks, the combination of an increase in lending volume and a reduction in the loan rate suggests that loan supply effects dominate loan demand effects. For large and foreign banks, loan supply effects are not a relevant feature of the monetary transmission mechanism or at least do not dominate demand effects.¹² Our finding that monetary policy initiates loan supply effects

¹¹Changes in the risk spreads may also reflect changes in banks' market power and sluggishness in the adjustment of lending rates to movements in the policy rate. Note that we focus on adjustment at business cycle or shorter frequencies for which market power can reasonably be assumed not to change much. Sluggish adjustment of lending rates to the policy rate would, *ceteris paribus*, lead to an increase in the spread after an expansionary monetary policy shock. Hence, we can interpret the decline of the spread as a decline in the risk premium.

¹²To test whether those loan and spread reactions are driven by the specificities of the STBL dataset, we include, as a check, 6 series capturing loan supply and demand from the Senior Loan Officer Opinion

only among small banks is in line with a large literature documenting the existence of the bank lending channel of monetary policy for small banks. In contrast, large banks (Kashyap and Stein 2000) and foreign banks (Cetorelli and Goldberg 2012) are able to isolate their lending activity from monetary policy shocks.

2.4.3 The Effects of Monetary Policy on Bank Risk Taking

We now turn to our main question of interest: changes in the composition of new loans in response to monetary policy shocks. These are given in Columns 2-5 of Figure 2.5(a) and 2.5(b). The definition of loan risk categories ensures that the quality of borrowers is held constant in response to macroeconomic shocks. Hence, shifts across loan risk categories that we observe should be driven by changes in loan supply of banks.

In the aggregate, the banking system significantly increases lending to the highest risk borrowers: aggregate new loans increase across all borrower groups with the exception of low risk borrowers. The increase in high risk loans is coupled with a strong reduction in the lending spread to these borrowers, suggesting that supply effects are the driving force.

We next compare the response of new loans to high risk borrowers with the response of new loans to minimal risk borrowers for all banks (Column 1 in Table 2.5(a)). There is no significant shift in the composition of loan supply from safe to risky loans after expansionary monetary shocks. The difference between new loans by all banks to high risk borrowers and new loans to low risk borrowers is even significantly negative. Hence, for the entire banking system, we do not find convincing evidence in favor of the hypothesis that the banking system engages in additional or excessive risk taking following expansionary monetary policy shocks. Our results instead suggest that, in the aggregate, there is a shift towards less risky borrowers.

Turning to the responses of the individual banking groups reveals some novel findings.

First, for the group of large domestic banks, only new loans to high risk borrowers increase in response to monetary policy shocks. The decline in the loan spread charged to high risk borrowers indicates the presence of loan supply effects for new loans to

Survey on Bank Lending Practices in the large dataset and re-estimate the model based on that dataset. We find both supply and demand effects after the expansionary monetary policy shocks: banks report a significant loosening of standards of lending to large/medium and small firms, and they report a stronger demand for C&I loans by large/medium and small firms. Moreover, loan spreads decline after the monetary policy shocks which is in line with our results for the STBL data and suggests that supply effects are relatively important.

high risk borrowers. This finding suggests that large banks shield their lending to lower risk borrowers at the expense of their lending to high risk borrowers. However, the difference between lending to minimal and high risk borrowers is virtually zero and not economically relevant (Table 2.5(a)). Hence, there is no additional risk taking by large banks.

Second, foreign banks reduce new loans to the group of high risk borrowers contemporaneously and significantly after the monetary policy shock. The composition of foreign banks' loan portfolio shifts significantly towards less risky borrowers (Table 2.5(a)).

Third, the story for small banks is very different from those for large and foreign banks. Small banks significantly increase lending to all borrower groups, except of lending to minimal risk borrowers (Table 2.5(a)). The increase in lending to high risk borrowers is very persistent. The lending response of small banks is significantly stronger than the responses of large and foreign banks for all but the lowest risk category (Table 2.5(b)). Loan spreads charged on high risk borrowers drop significantly on impact. Both, the lending response and the spread responses for small banks are significant. Hence, following expansionary monetary policy shocks, small banks tilt their credit portfolio from low risk to high risk borrowers and charge a lower risk spread. Accordingly, a risk-taking channel of monetary policy is operative for the group of small banks.

Our finding that monetary policy shocks initiate risk taking only for the smaller banks is consistent with the view that banks which are opaque and which are most prone to agency problems react most strongly to monetary policy shocks. Due to fixed costs of monitoring and weaker disclosure requirements, smaller banks tend to face more severe agency problems. This, *inter alia*, affect their access to external funding. This is also indirectly documented by the balance sheet composition of small banks versus large and foreign banks. Bank level data from the US Call Report show that, small banks have, on average, higher capital and liquidity shares than large and global banks: over our sample period, small banks had a median capitalization ratio (liquidity ratio) of 9.5% (24.6%). Large and global banks had lower median capitalization ratios (liquidity ratios) of 8.6% (21.4%) and 8.4% (21.9%), respectively. (Unreported) cross-sectional regressions of bank size on capitalization ratios and on liquidity ratios confirm the negative relation between size and measures of agency problems.

2.4.4 Adjustment of Additional Loan Contract Terms

So far, our focus has been on changes in lending across risk categories and on the risk spread. Our dataset provides us with two additional variables which can be used to assess changing risk patterns. These variables are the degree of collateralization and the maturity structure of new loans. The classification of loans into different risk categories used so far is based on the quality, not the quantity, of collateral. Also, the maturity of loans is not reflected in the risk rating. Increased collateralization or shorter maturities would make loan portfolios less risky, and banks could use these contract terms in order to - subsequently - take on more risk (Strahan 1999).

We focus on lending to high risk borrowers by small banks for which the risk-taking channel was found to be active.¹³ Our results show that small banks lower the maturity of and increase the collateral for high risk loans following monetary policy shocks, possibly as a pre-requisite for risk taking (Figure 2.6). This interpretation is supported by the timing of the effects: the effect on loans builds up only gradually but the reactions of collateral and maturity are more frontloaded.

In response to lower policy rates, banks may also change the riskiness of their activities by changes the composition of their funding sources. *Ceteris paribus*, increased leverage tends to increase bank risk. Yet, the STBL survey does not provide information on bank leverage. Merging data from other sources of information would add measurement error to our data. To nevertheless control for banks' liabilities, we have added, as a robustness check, capital ratios for the entire banking system and the three banking groups taken from the US Call Reports. Our main results (available on request) do not change.

2.4.5 Testing the "Too-Low-For-Too-Long" Hypothesis

Our analysis so far has assumed that the monetary policy regime has remained fairly constant during the sample period. According to Taylor (2008) and Taylor (2013), monetary policy interest rates deviated importantly from the usual policy rule between 2003-2005 in the US (possibly because the Federal Reserve aimed at avoiding deflation after the burst of the dotcom bubble).¹⁴ This has led researchers to assess whether

¹³Results for other banking groups and risk categories are available upon request.

¹⁴Eickmeier and Hofmann (2013) use a linear model and look at the impact of a monetary policy loosening on credit risk spreads and mostly focus on the pre-crisis boom period in the US. Bogdanova

risk taking is particularly pronounced when interest rates are at low levels for extended periods of time, i.e. when they are 'too low for too long'. Altunbas, Gambacorta, and Marques-Ibanez (2012), for example, find various measures of the Taylor-rule gap, i.e. the deviations of the monetary policy rate from the rate implied by various Taylor rules or from the natural interest rates, to explain banks' risk taking.¹⁵

To test the hypothesis whether risk taking takes place primarily or exclusively in prolonged periods of too low interest rates, we extend our model (1) to allow the banking variables included in X_t to react differently to movements in the policy rate in the 'too-low-for-too-long' period compared to the rest of the sample period:

$$\begin{aligned} x_{jt} &= [\lambda_j^{F-MP'} \lambda_j^{(1)MP'}]' F_t + e_{jt} \quad \text{for } t < \tau_1 \\ x_{jt} &= [\lambda_j^{F-MP'} \lambda_j^{(2)MP'}]' F_t + e_{jt} \quad \text{for } \tau_1 \leq t \leq \tau_2 \\ x_{jt} &= [\lambda_j^{F-MP'} \lambda_j^{(1)MP'}]' F_t + e_{jt} \quad \text{for } t > \tau_2. \end{aligned} \tag{2.4.3}$$

$\lambda_j^{F-MP'}$ represents the $(r-1) \times 1$ vector of loadings for variable j associated with all (observable and latent) factors with the exception of the monetary policy rate. Those loadings are still constant over time. $\lambda_j^{(k)MP'}$ is the scalar loading of the j^{th} variable associated with the policy rate, which differs across regimes $k = 1, 2$. Hence, the banking variables' reactions to movements in the policy rate are regime dependent, and the 'too-low-for-too-long' period is taken as given as the period when monetary policy was excessively accommodative according to Taylor (2013): $\tau_1 = 2003Q1$ to $\tau_2 = 2005Q4$.¹⁶

We first estimate the factors with PCs applied to the whole sample. This is a valid approach given the results by Bates, Plagborg-Møller, Stock, and Watson (2013) who show that factors can be estimated consistently with PCs even in the presence of structural breaks in the loadings.¹⁷

To estimate the loadings, we then regress each of the banking variables on the latent and observable factors as well as on the Federal Funds rate interacted with a dummy variable which equals 1 in the 2003-2005 period and 0 otherwise. The remaining steps

and Hofmann (2012) look at the 'Great Deviation', i.e. deviations of policy rates from rates implied by the Taylor rule at the global level.

¹⁵Ioannidou, Ongena, and Peydro (2009) and Jimenez, Ongena, Peydro, and Saurina (forth.) also find that risk taking is particularly large when the level of the Federal Funds rate is low.

¹⁶Results are not very sensitive to the exact dating of the 'too-loo-for-too-long' period.

¹⁷See Bates, Plagborg-Møller, Stock, and Watson (2013) for details on the conditions for consistent factor estimation in the presence of breaks in the loadings and Monte Carlo simulation results.

are the same as before. We generate two sets of impulse response functions, conditional on the two regimes characterizing the stance of monetary policy.^{18, 19} Figure 2.7 shows impulse responses for the 'too-low-for-too-long' period (in red) and the 'normal' period (in blue), and Table 2.6 computes our relevant measures for risk taking for different groups of banks for the two regimes.

Results for the normal regime are quite similar to the results for the constant parameter model presented above. Loan impulse responses to a (same-sized) monetary policy shock, however, notably differ over the 2003-2005 period compared to the normal period. Differences in spread responses between the two periods are barely visible. Table 2.6 reveals that, in the 2003-2005 period, additional risk taking is now not only found for small, but also for foreign banks. Spreads charged on high risk loans decline for small and foreign banks, indicating that these banks do not compensate additional risk taking in new loans by charging higher risk premia. As for the entire sample period, we do not find evidence for risk taking by large domestic banks.

The result of additional risk taking by foreign banks in response to an expansionary monetary policy shock over the 'too-low-for-too-long' period supports results by Bruno and Shin (2012) and Shin (2012). Those authors emphasize the role of large European banks in fueling the lending boom in the mid-2000s. They argue that easy monetary policy in the US and a regulatory structure in Europe that allowed high leverage enabled European banks to take on excessive risk in the US. The anecdotic evidence provided in Shin (2012) shows that foreign banks used cheap short term US-Dollar funding to invest into toxic assets generated by the shadow banking system. Our finding complements these results by showing that risk taking by those banks was not only confined to the security markets segment but took also place in the traditional business lending segment.

2.5 Conclusion

Expansionary monetary policy is one main culprit for the excessive build-up of risk in the US banking industry in the run up to the global financial crisis. This observation has led to the recommendation that monetary authorities should explicitly consider as-

¹⁸Hence, unlike in some of the related threshold-VAR literature (which relies on generalized impulse response functions) we assume that shocks cannot caused regimes changes.

¹⁹There are certainly other ways to test the hypothesis of risk taking being particularly pronounced in periods of very loose monetary policy. We decided to use a parsimonious model, given our short sample period.

pects of financial, and in particular banking sector, stability when deciding on monetary policy actions. Yet, previous literature has not given a clear answer to the question whether expansionary monetary policy increases or decreases the risk of banks. Differences across studies partly owe to the level of aggregation of the data and partly owe to the measurement of risk.

With this paper, we inform the debate about the effects of monetary policy on the risk-taking decisions of commercial banks. Using a factor-augmented vector-autoregressive model (FAVAR), we exploit information on the riskiness of banks' new loan origination provided by the Federal Reserve's *Survey of Terms of Business Lending*. These data allow analyzing new loans and thus risk-taking behavior of banks. In this sense, we realign previous micro-level studies, which allow measuring risk taking of banks, with macro studies, which identify monetary policy and other macroeconomic shocks. In addition, we analyze heterogeneity in the response to monetary policy shocks across different banking groups.

Our strategy to identify a risk-taking channel of monetary policy exploits heterogeneity in the responses of new loans and loan spreads. We compare adjustments across different types of banks and different loan risk categories within the same banking group. We show that loan supply effects dominate loan demand effects after monetary policy shocks for small banks. Yet, we cannot fully exclude the possibility that the composition of loan demand might shift as well, i.e. that more or less risky borrowers demand loans after the shocks. Insofar, our estimates should be seen as an upper bound of the supply driven risk-taking channel of monetary policy.

Our research has three main findings.

First, on average over the sample period, we do not find evidence supporting the risk-taking channel hypothesis for the groups of large and foreign banks. By contrast, our analysis reveals an active risk-taking channel of monetary policy among the group of small banks. Small banks significantly increase new loans to high risk borrowers after expansionary monetary policy shock. The composition of loan supply of small banks shifts towards more risk taking. Furthermore, this shift in the risk composition of the portfolio of new loans is not compensated by an increase in the risk premia. Small banks rather shift their (new) loan portfolios towards higher risk loans *and* charge a lower risk premium.

Second, in order to dig deeper into the risk-taking behavior of small banks, we also investigate the behavior of non-price and non-quantity features of the loan contract

terms. We show that small banks tend to lower the maturity of high-risk loans following monetary policy shocks. These new loans are more likely backed by collateral. This suggests that small banks take into account the additional risk of new loans by adjusting other loan contract terms, possibly as a pre-requisite for risk taking.

As a final, third, contribution to the literature, we test the hypothesis that risk taking in banking is particularly pronounced when interest rates are 'too-low-for-too-long'. Our findings reveal that, in the 'too-low-for-too-long' period, additional risk taking is now not only found for small, but also for foreign banks. The result of additional risk taking by foreign banks in response to an expansionary monetary policy shock over the 'too-low-for-too-long' period supports results by Shin (2012), who argues that especially foreign banks used excess liquidity in the mid-2000s to take on excessive risk.

Overall, the FAVAR methodology used in this paper provides a powerful tool for analyzing heterogeneity with regard to banks' responses to monetary policy shocks. Ignoring heterogeneous responses or the feedback between the banking sector and the macroeconomy may lead to erroneous conclusions concerning the link between risks in banking and the macroeconomy. Applying this methodology to questions of systemic risk in banking or for the analysis of changed capital requirements would be an important step for future research.

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2.7 Tables and Figures

Table 2.1: Summary Statistics

This Table shows summary statistics for the different types of banks. The interest rate spread refers to the difference of the banking group's lending rate in the respective risk category with the 1-year constant maturity Treasury bill rate.

(a) Log Changes in Volume of New Loans

	All Banks		Large Domestic Banks		Small Domestic Banks		Foreign Banks	
	median	s.d.	median	s.d.	median	s.d.	median	s.d.
All Loans	0.01	0.17	0.03	0.20	0.01	0.20	-0.02	0.19
Minimal Risk	-0.04	0.60	0.01	0.72	0.06	0.55	-0.09	0.87
Low Risk	-0.02	0.24	0.04	0.32	-0.00	0.41	-0.02	0.41
Moderate Risk	-0.01	0.19	-0.00	0.19	0.00	0.20	0.00	0.29
High Risk	-0.00	0.20	0.01	0.23	0.02	0.35	0.05	0.26

(b) Interest Rate Spread on New Loans

	All Banks		Large Domestic Banks		Small Domestic Banks		Foreign Banks	
	median	s.d.	median	s.d.	median	s.d.	median	s.d.
All Loans	1.66	0.79	1.76	0.82	3.21	0.83	1.07	0.82
Minimal Risk	0.69	0.85	0.7	0.95	2.48	1.02	0.56	0.8
Low Risk	1.15	0.82	0.87	0.88	2.74	1.04	0.87	0.84
Moderate Risk	1.76	0.83	1.83	0.81	3.45	0.9	1.18	0.89
High Risk	2.31	0.86	2.7	0.84	3.64	0.84	1.56	0.96

Table 2.2: Correlation of the First 5 Unpurged Latent Banking Factors with Macroeconomic Variables

This table shows the correlation of the first 5 raw (or unpurged) principal components extracted from the banking data set with the observable macroeconomic variables. See Section 3.2 for details.

	PC 1	PC2	PC3	PC4	PC5
GDP growth	0.42	-0.21	0.26	-0.18	-0.16
GDP deflator inflation	-0.52	-0.17	0.33	-0.16	0.14
Federal funds rate	0.56	0.47	-0.01	-0.45	-0.01

Table 2.3: Cumulated Variance Shares Explained by the Common Factors

This table shows the cumulated variance shares explained by first r^* unpurged latent factors extracted from the banking dataset and the cumulated variance shares explained by the first r^* purged latent factors and observables. See Section 3.2 for the details.

	Unpurged Factors	Purged Latent Factors + Observables
r^*		
1	0.17	0.29
2	0.31	0.4
3	0.42	0.47
4	0.48	0.53
5	0.54	0.57

Table 2.4: Variance Explained by the Common Factors

This table shows the fraction of variance of new loan growth and loan spreads explained by the observed and latent purged factors.

	All Loans	Minimal Risk	Low Risk	Moderate Risk	Acceptable Risk
<i>New Loan Growth</i>					
All Banks	0.27	0.17	0.14	0.28	0.09
Large Banks	0.19	0.19	0.14	0.21	0.09
Small Banks	0.16	0.03	0.11	0.27	0.09
Foreign Banks	0.22	0.04	0.04	0.19	0.08
<i>Loan Spreads</i>					
All Banks	0.88	0.73	0.72	0.88	0.73
Large Banks	0.86	0.61	0.75	0.82	0.77
Small Banks	0.84	0.37	0.67	0.82	0.79
Foreign Banks	0.79	0.62	0.47	0.84	0.58

Table 2.5: Difference between Impulse Responses of Loans After Monetary Policy Shocks

The table displays differences in impulse responses after expansionary monetary policy shocks. Entries in bold indicate that the differences are significant at the 90% level.

(a) Differences between Acceptable and Minimum Risk Categories				
	All Banks	Small Banks	Large Banks	Foreign Banks
<i>New loans</i>				
		Monetary Policy Shock		
Impact effect	-0.006	0.007	0.000	-0.003
Four quarters	-0.035	0.037	-0.019	-0.014
<i>Loan spreads</i>				
		Monetary Policy Shock		
Impact effect	-0.003	-0.015	0.011	-0.005
Four quarters	0.006	-0.004	0.008	0.000
(b) Differences between Acceptable and Minimum Risk Categories				
	Minimum Risk	Low Risk	Moderate Risk	Acceptable Risk
<i>New loans</i>				
		Impact effect		
Small – Large	-0.004	0.004	0.004	0.004
Small – Foreign	-0.001	0.006	0.000	0.009
Large – Foreign	0.003	0.001	-0.004	0.006
		Four quarters		
Small – Large	-0.04	0.031	0.006	0.016
Small – Foreign	-0.006	0.047	-0.016	0.045
Large – Foreign	0.032	0.016	-0.023	0.028
<i>Loan spreads</i>				
		Impact effect		
Small – Large	0.026	0.03	0.015	0.000
Small – Foreign	0.022	0.026	0.033	0.011
Large – Foreign	-0.004	-0.004	0.018	0.012
		Four quarters		
Small – Large	0.006	0.000	0.001	-0.005
Small – Foreign	0.003	-0.002	0.012	0.000
Large – Foreign	-0.003	-0.003	0.011	0.006

Table 2.6: Difference between Impulse Responses of Loans After Monetary Policy Shocks Using a FAVAR with Time-varying Loadings

The table displays differences in impulse responses after expansionary monetary policy shocks. Entries in bold indicate that the differences are significant at the 90% level. T-L-T-L = too-low-for-too-long regime.

(a) Differences between Acceptable and Minimum Risk Categories (Normal Regime)

	All Banks	Small Banks	Large Banks	Foreign Banks
<i>New Loans</i>				
Monetary policy shock				
Impact effect	-0.009	0.007	-0.007	0.000
Four quarters	-0.055	0.033	-0.068	0.008
<i>Loan spreads</i>				
Monetary policy shock				
Impact effect	0.000	-0.012	0.016	-0.003
Four quarters	0.011	-0.002	0.012	0.002

(a) Differences between Acceptable and Minimum Risk Categories (T-L-T-L Regime)

	All Banks	Small Banks	Large Banks	Foreign Banks
<i>New Loans</i>				
Monetary policy shock				
Impact effect	-0.021	0.001	-0.04	0.019
Four quarters	-0.097	0.017	-0.179	0.072
<i>Loan spreads</i>				
Monetary policy shock				
Impact effect	0.021	0.008	0.034	0.009
Four quarters	0.016	0.004	0.017	0.005

Figure 2.1: Macroeconomic Variables and Latent "Banking" Factors

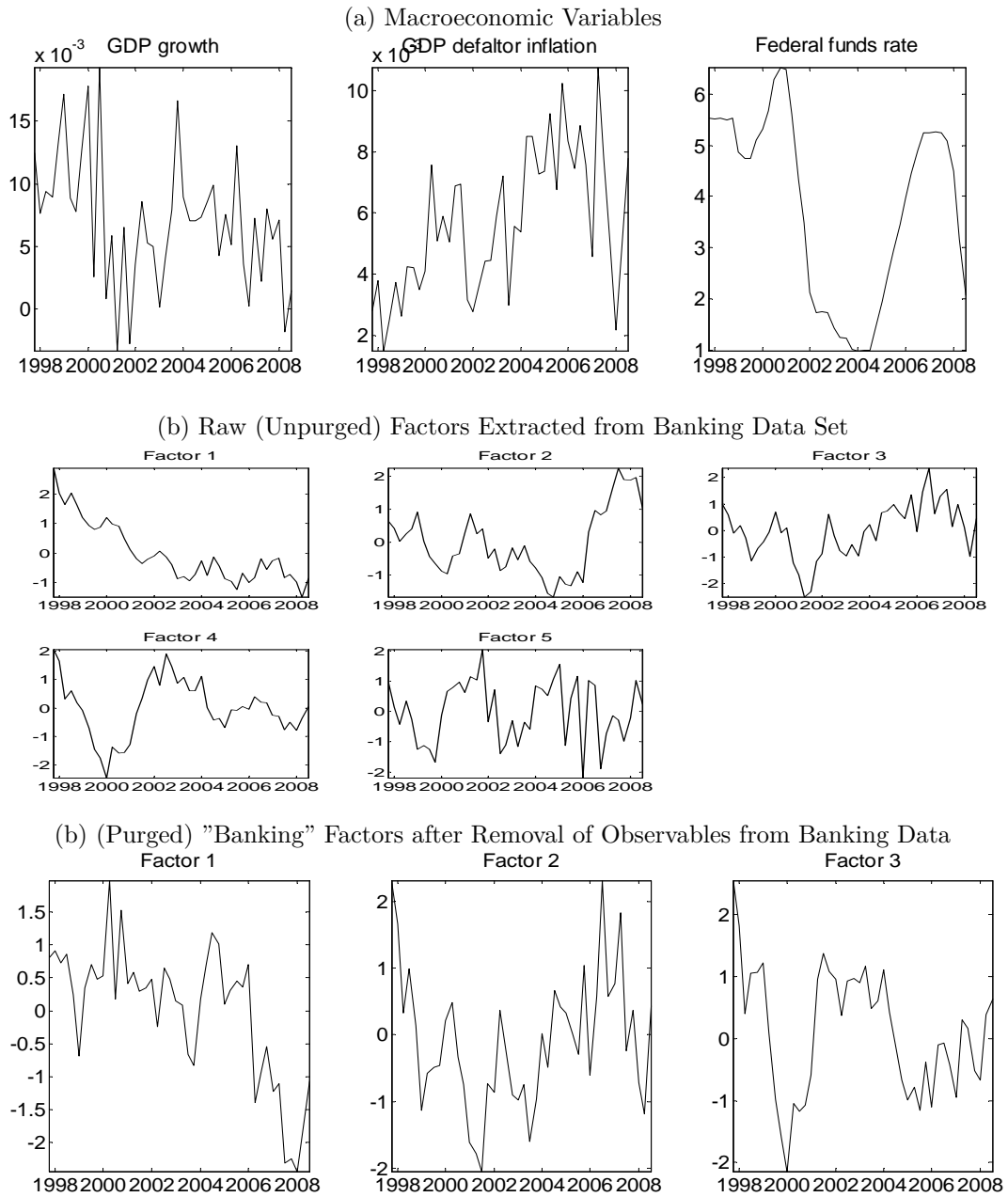


Figure 2.2: New Loans from the STBL in Comparison with Loans from Other Sources

The red dotted line shows the change in outstanding commercial and industrial loans from the Federal Reserve Statistical Release H8 (right scale). The black solid line shows new loans from the Survey of Terms of Business Lending (left scale). The blue dashed line shows new loans from the DealScan database taken from Ivashina and Scharfstein (2010) which starts in 2000 (left scale). All series are seasonally adjusted and expressed in real terms (new loans are indexed, 2000Q1:1)

(a) Reaction of New Lending

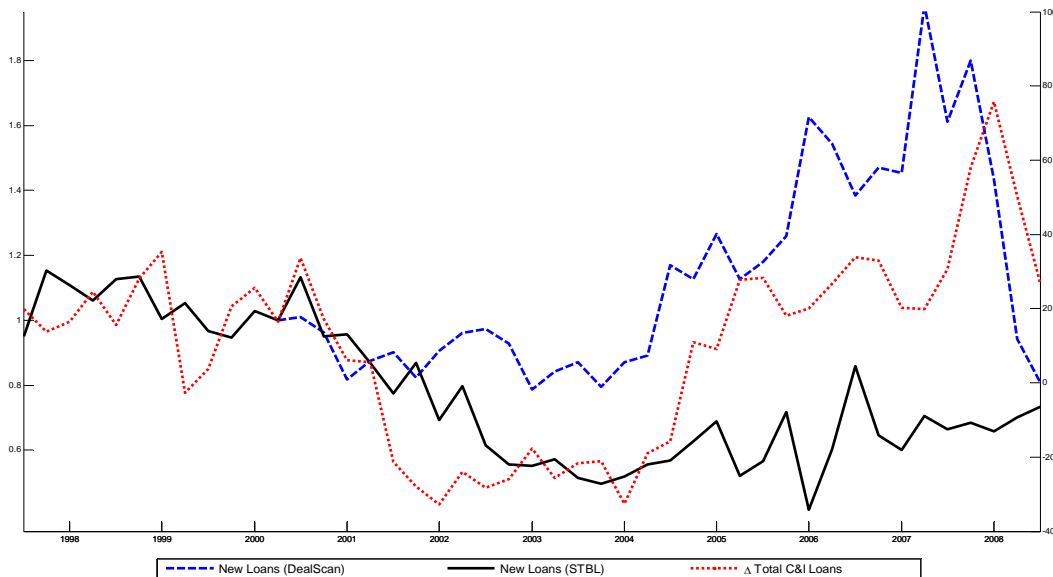
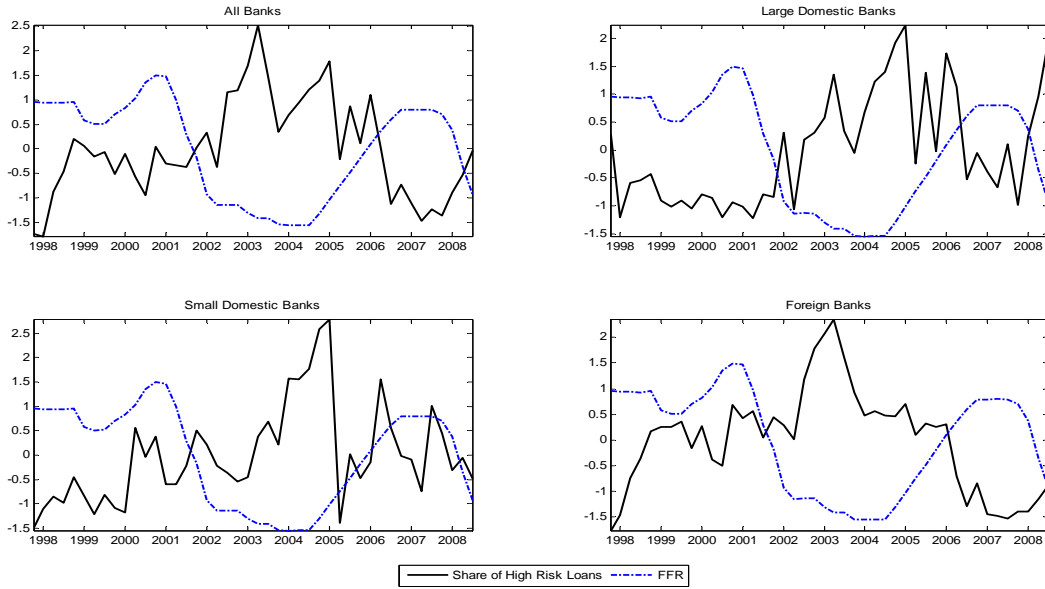


Figure 2.3: High Risk Lending and the Federal Funds rate

(a) Share of High Risk Loans and the Federal Funds Rate



(b) Loan Spread on High Risk Loans and the Federal Funds Rate

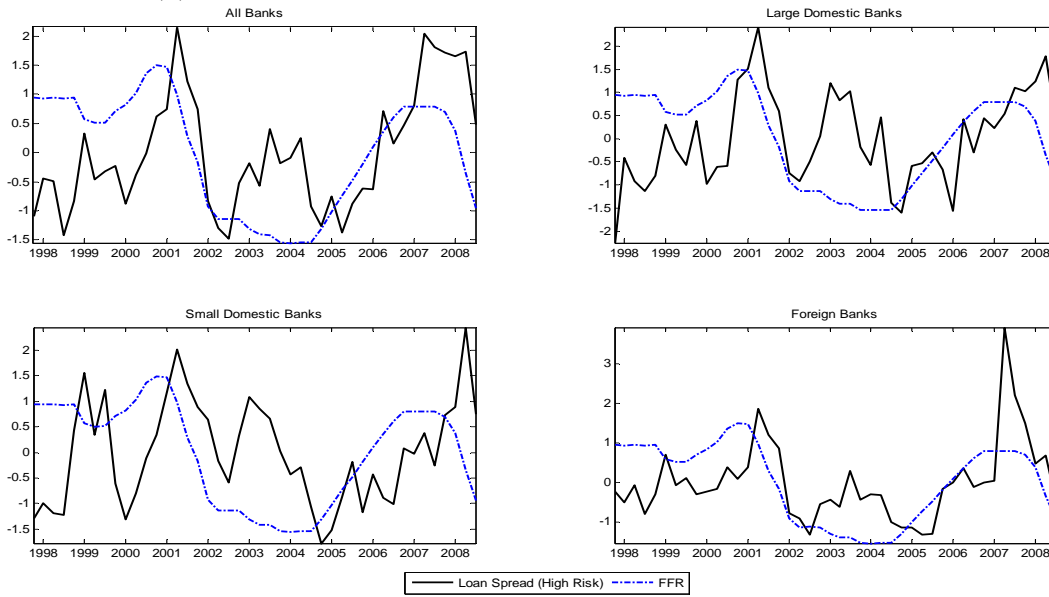


Figure 2.4: Effect of Monetary Policy Shocks on Macroeconomic Variables

This figure shows median impulse responses (black lines) together with 68% confidence bands (dark blue shaded area) and 90% confidence bands (light blue shaded area) to a one standard deviation monetary policy shock.

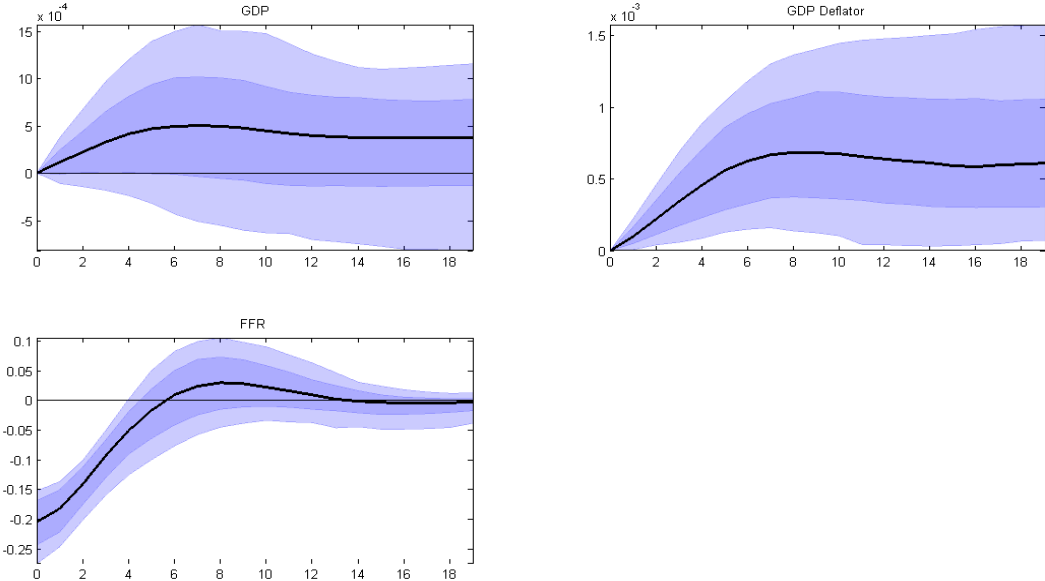


Figure 2.5: Effect of Monetary Policy Shocks on New Lending and Loan Spreads

This figure shows median impulse responses (black lines) together with 68% confidence bands (dark blue shaded area) and 90% confidence bands (light blue shaded area) of new lending (panel (a)) and loan rates (panel (b)) to a one standard deviation monetary policy shock.

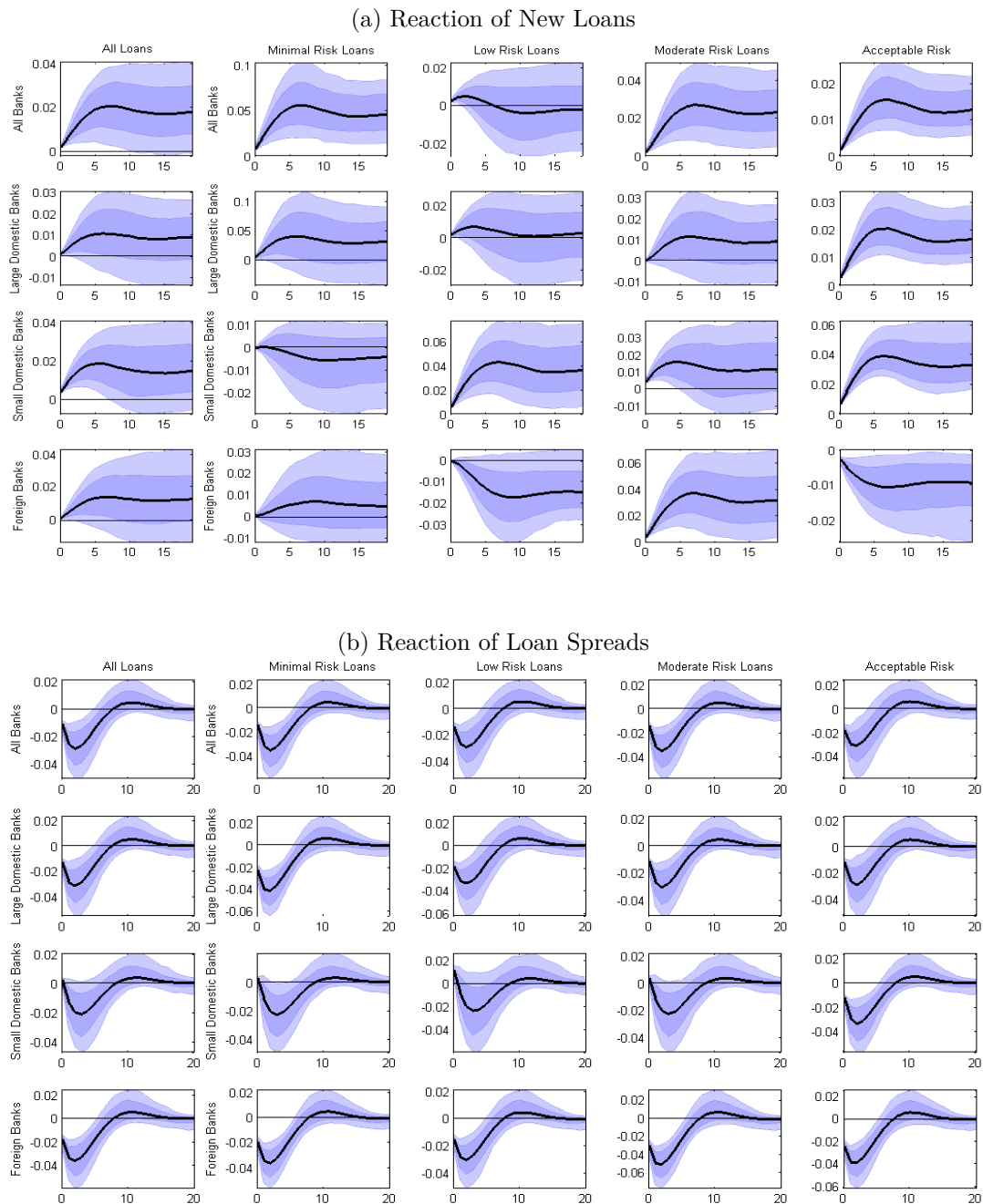


Figure 2.6: Effect of Monetary Policy Shocks on Collateralization and Loan Maturity of New High Risk Lending by Small Banks

This figure shows median impulse responses (black lines) together with 68% confidence bands (dark blue shaded area) and 90% confidence bands (light blue shaded area) of collateral (panel (a)) and maturity (panel (b)) to a one standard deviation monetary policy shock.

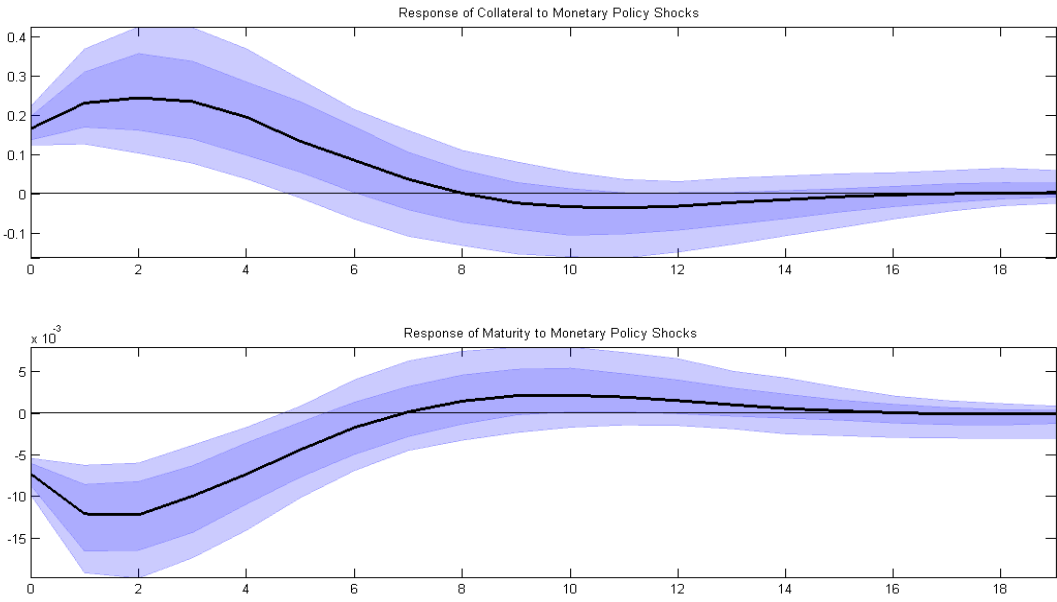
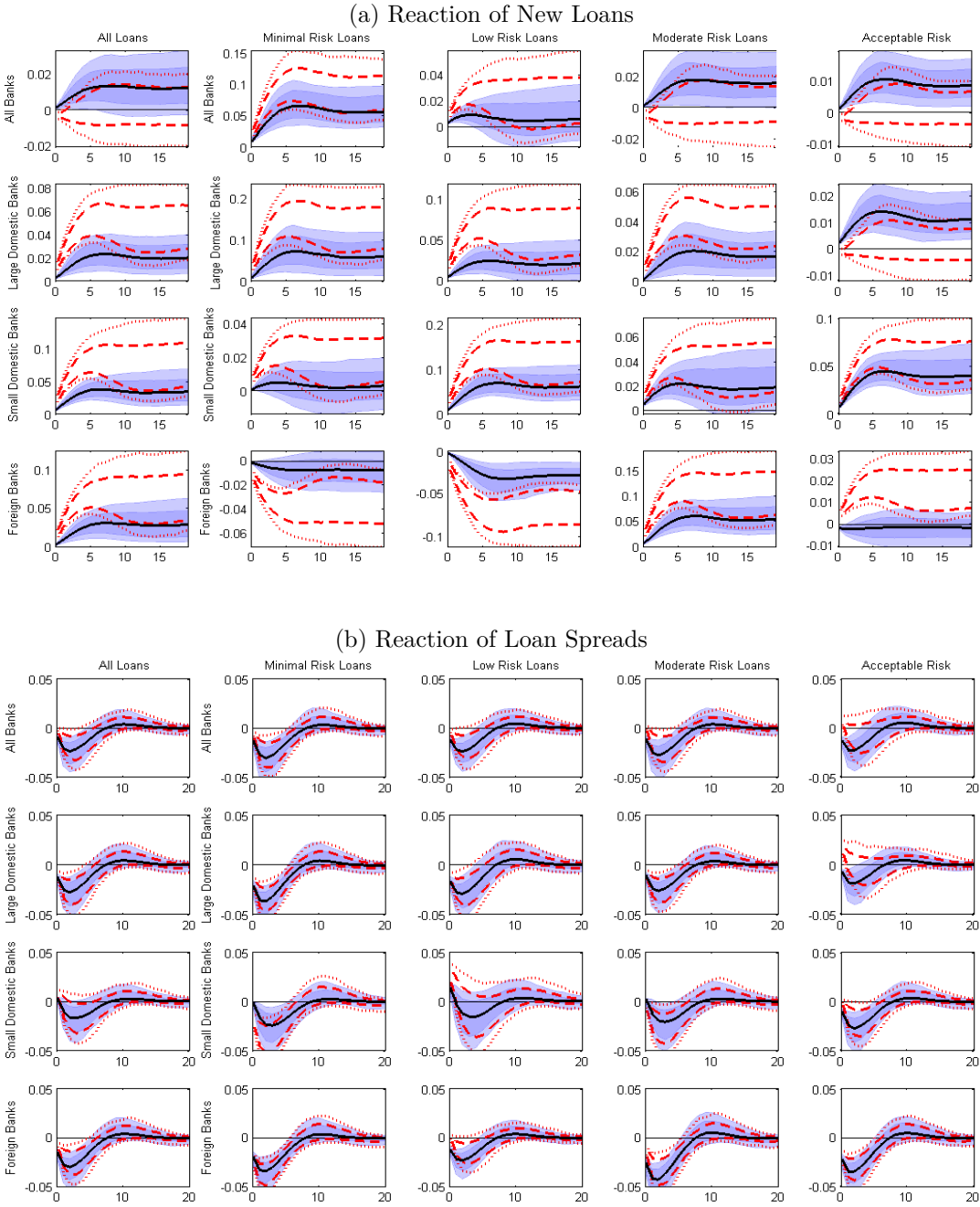


Figure 2.7: Effect of Monetary Policy Shocks on New Lending and Loan Spreads - Baseline vs. FAVAR with Time-varying Loadings

This figure shows median impulse responses (black lines) together with 68% confidence bands (dark blue shaded area, red dashed lines) and 90% confidence bands (light blue shaded area, red dashed lines) of new lending (panel (a)) and loan rates (panel (b)) to a one standard deviation monetary policy shock. Blue shaded correspond to the 'normal monetary policy regime', while the red lines correspond to 'too-low-for-too-long monetary policy regimes'



2.8 Appendix to Chapter 2

Data Appendix

This appendix provides the classification of loan risk according to the Survey of Terms of Business Lending. The following information is based on the instructions (FR 2028A), last updated December 11, 2008.

Minimal Risk

Loans in this category have virtually no chance of resulting in a loss. They would have a level of risk similar to a loan with the following characteristics:

- The customer has been with your institution for many years and has an excellent credit history.
- The customer's cash flow is steady and well in excess of required debt repayments plus other fixed charges.
- The customer has an AA or higher public debt rating.
- The customer has excellent access to alternative sources of finance at favorable terms.
- The management is of uniformly high quality and has unquestioned character.
- The collateral, if required, is cash or cash equivalent and is equal to or exceeds the value of the loan.
- The guarantor, if required, would achieve approximately this rating if borrowing from your institution.

Low Risk

Loans in this category are very unlikely to result in a loss. They would have a level of risk similar to a loan with the following characteristics:

- The customer has an excellent credit history.
- The customer's cash flow is steady and comfortably exceeds required debt repayments plus other fixed charges.
- The customer has a BBB or higher public debt rating.
- The customer has good access to alternative sources of finance at favorable terms.
- The management is of high quality and has unquestioned character.
- The collateral, if required, is sufficiently liquid and has a large enough margin to make very likely the recovery of the full amount of the loan in the event of default.
- The guarantor, if required, would achieve approximately this rating if borrowing from your institution.

Moderate Risk

Loans in this category have little chance of resulting in a loss. This category should include the average loan, under average economic conditions, at the typical lender. Loans in this category would have a level of risk similar to a loan with the following characteristics:

- The customer has a good credit history.
- The customer's cash flow may be subject to cyclical conditions but is adequate to meet required debt repayments plus other fixed charges even after a limited period of losses or in the event of a somewhat lower trend in earnings.
- The customer has limited access to the capital markets.
- The customer has some access to alternative sources of finance at reasonable terms.
- The firm has good management in important positions.
- Collateral, which would usually be required, is sufficiently liquid and has a large enough margin to make likely the recovery of the value of the loan in the event of default.
- The guarantor, if required, would achieve approximately this rating if borrowing from your institution.

Acceptable Risk/Others

Loans in this category have a limited chance of resulting in a loss. They would have a level of risk similar to a loan with the following characteristics:

- The customer has only a fair credit rating but no recent credit problems.
- The customer's cash flow is currently adequate to meet required debt repayments, but it may not be sufficient in the event of significant adverse developments.
- The customer does not have access to the capital markets.
- The customer has some limited access to alternative sources of finance possibly at unfavorable terms.
- Some management weakness exists.
- Collateral, which would generally be required, is sufficient to make likely the recovery of the value of the loan in the event of default, but liquidating the collateral may be difficult or expensive. - The guarantor, if required, would achieve this rating or lower if borrowing from your institution.

Chapter 3

Time-Variation in Macro-Financial Linkages

3.1 Introduction

The Great Recession in 2008/2009 was triggered by major turbulences on financial markets. The macroeconomic models commonly used in academic research and in policy institutions were unable to explain the strong economic downturn following these turmoils. Two main shortcomings of the standard approach have been identified: the lack or insufficient modeling of financial variables in these models and the lack of a time-varying relationship between the macroeconomy and the financial sector. This has been expressed by the Vice Chairman of the Federal Reserve Donald L. Kohn in 2009 at the Federal Reserve Conference on Key Developments in Monetary Policy where he stated: "The various mechanisms that have tended to amplify asset price movements and the feedback among those movements, credit supply, and economic activity were not well captured by the models used at most central banks." Moreover, he identified "[...] the need for models to take much better account of nonlinearities and tail events [...]".¹

This chapter is based on joint work with Sandra Eickmeier and Massimiliano Marcellino entitled "Time-Variation in Macro-Financial Linkages".

¹Similarly, the Member of the Executive Board of the European Central Bank Benoit Coeure argued in 2012 at an international conference on "Macroeconomic Modelling in Times of Crisis": "Models need to incorporate at least some of the key aspects of, and key players in, the financial crisis" and he lists, among others, financial factors and intermediaries.

Based on a model, which does not suffer from these shortcomings, we address the following questions. How important is the financial sector as a source of shocks for GDP growth? Can we detect changes over time? If, yes, has the propagation of financial shocks to growth or the size of the shocks or both changed over time? How does the Global Financial Crisis compare to previous crises (is "this time different"), and why is the recovery from the Great Recession so weak and slow?

We incorporate a few key financial indicators in an otherwise standard Bayesian macroeconomic vector autoregressive model (VAR) for the US and estimate that model over the period 1958Q1-2012Q2. The VAR includes GDP growth, GDP deflator inflation, house price inflation, the corporate bond spread, stock price inflation and the Federal Funds rate.² In order to account for possible time variation in the relationship between financial indicators and the macroeconomy we estimate the VAR allowing for changes in the shock volatilities, the autoregressive coefficients and the contemporaneous relations between the variables. This allows us to capture both gradual, long-lasting changes in macro-financial linkages, which arise as a consequence of deep structural changes, as well as asymmetries over the business or the financial cycle related to financial frictions. Based on our estimated time-varying parameter VAR (TV-VAR), we examine the sum of the contributions of shocks to each individual financial indicator to GDP growth as a measure of the overall importance of the financial sector as origin of shocks for the macroeconomy and then shed light on the underlying sources of time variation. Finally, we compare financial shock contributions estimated from the TV-VAR with those estimated from a constant parameter VAR (C-VAR) and a VAR in which we replace the financial variables with the National Financial Conditions Index (NFCI) published by the Federal Reserve Bank of Chicago.

Our main findings are: (i) Over the Great Recession, the explanatory power of financial shocks for GDP growth rose to roughly 50 percent, compared to 20 percent in normal times. House price shocks were very important in explaining the Great Recession, accounting for about 2/3 of the overall contribution of the financial sector to GDP growth. House price and credit spread shocks have been larger and the transmission to growth stronger than previously.

²The house price is, strictly speaking, not a financial variable, but an asset price. The Federal Funds rate is driven by monetary policy which we will account for as well. For simplicity we label all variables (including house prices and the Federal Funds rate) included in the VAR "financial variables" throughout the paper.

(ii) The slow and weak recovery from the Global Financial Crisis is due to negative developments in the housing market, probably due to households being still credit constrained. The C-VAR does not generate negative financial shock contributions at the end of the sample period. A constant parameter model which includes the Chicago Fed's NFCI, however, does. This suggests that a model which includes a large number of financial variables can also capture the complex dynamic interactions of financial markets and the macroeconomy, which we pick up by our time-varying parameter model.

(iii) As concerns the pre-Global Financial Crisis period, we detect significantly positive contributions of credit spread shocks to GDP growth in the mid-1980s, probably reflecting the process of financial deregulation. Moreover, we find significantly negative financial shock contributions around two other banking crises, the Bank Capital Squeeze in the early-1970s and the Savings and Loan crisis in the late-1980s/early-1990s, due to particularly large credit spread and housing shocks, respectively. The stock market crashes in 1987 and 2001 did not have significantly negative real effects.

(iv) Finally, the housing sector affects the macroeconomy asymmetrically. Negative shocks tend to be more important for the macroeconomy than positive shocks, as has been recently suggested by Guerrieri and Iacoviello (2012). Moreover, we find a trend increase in the transmission and in the size of housing shocks since the early-2000s, probably due to a rise in housing wealth and extended mortgage lending.

The remainder of the paper is organized as follows. In Section 3.2 we relate our paper to the literature and discuss our original contributions. In Section 3.3 we present the data, and in Section 3.4 the methodology. In Section 3.5, we provide results on the time-varying macro-financial linkages. First, we analyze the overall contribution of structural financial sector shocks to GDP growth, and then we assess the contributions of unexpected changes in the individual financial variables. We shed light on the contributions' determinants, i.e. changes over time in the impact of shocks to individual financial indicators to GDP growth and in the volatility of these shocks. We then compare the outcomes from the TV-VAR with those from the C-VAR and from a time-varying VAR which includes the NFCI instead of the observable financial variables and carry out further robustness checks. In Section 3.6 we summarize the main findings and conclude.

3.2 Related Literature

There is a growing, but still small, empirical literature which looks at the role of financial variables for the macroeconomy in a time-varying parameter setup. Time series applications for the US include Balke (2000), Davig and Haikko (2010), Kaufmann and Valderrama (2010), Guerrieri and Iacoviello (2012), Hubrich and Tetlow (2012), Nason and Tallman (2012), Eickmeier, Lemke, and Marcellino (2011b), Ciccarelli, Ortega, and Valderrama (2012) and Gambetti and Musso (2012). Some of these papers assume that parameters can differ across states of the economy and use Markov switching, threshold VARs or a dummy variable approach. Others allow parameters to evolve smoothly over time, in similar ways as we do here. Most papers allow both shock variances and coefficients to change. Moreover, most studies include a few observed financial variables whereas others use a composite index formed out of a larger number of financial variables (a "financial conditions index" (FCI) or a "financial stress index"). Most papers focus on a particular financial shock or a shock to the composite index, whereas only a few papers consider more than one particular financial shock. An overview of previous work (including work for countries other than the US) is presented in Figure 3.1.

Results on whether the transmission of financial shocks is time-dependent or not are mixed. However, what emerges from basically all studies is that the size of financial shocks is changing over time. This possibly reflects that in financial crisis periods, financial shocks hit a particularly large number of financial market segments at the same time or that credit defaults multiply. This finding is also consistent with Stock and Watson (forth.) who focus on the sources of the Great Recession in the US. They find that relatively large shocks rather than changes in the transmission can explain the Great Recession. Their analysis is based on a dynamic factor model with constant parameters, but they consider 2007 as a break point. Finally, our paper is related to recent empirical evidence by Del Negro and Schorfheide (2013) who suggest that financial frictions may matter more over financial crisis periods than in normal times. The authors show that a DSGE model with financial frictions delivers better out-of-sample forecasts than a DSGE model without these features since 2008. By contrast, over most of the rest of their sample period (starting in 1994) the simple model without financial frictions yields better forecasts.

Compared to the literature surveyed above our approach has two desirable features. First, our TV-VAR is relatively flexible compared to some of the specifications used in

the surveyed literature. The changing autoregressive coefficients capture possible time variation in the propagation of shocks, while the time-varying innovation covariance matrix picks up changes in shock sizes and simultaneous relations among the variables. Hence, our model can account for gradual, long-lasting changes in the transmission of financial shocks to the macroeconomy, due to, for example, financial innovations, globalization or regulatory changes on financial markets. In addition the model can capture asymmetries in the effects of financial shocks over time, due to agency problems between lenders and borrowers, which are typically more pronounced in financial crises periods. Agency problems occur, for instance, when collateralized loans are granted. When asset prices fall, lending is accordingly also constrained (Kiyotaki and Moore 1997, Guerrieri and Iacoviello 2012). Furthermore, greater information asymmetry between lenders and borrowers in crisis periods can drive up the cost of obtaining external funding (Bernanke, Gertler, and Gilchrist 1999).³ Our model can also account for possible changes in the financial shock transmission due to a changing conduct of monetary policy or the zero lower bound of nominal interest rates and measures of unconventional monetary policy.

Second, the financial variables we include in our model cover the most relevant features of the financial sector, and are closely related to key concepts in DSGE models with financial frictions.⁴ House and stock prices capture housing and financial wealth, and asset price movements can affect the real sector of the economy through wealth effects (Campbell and Cocco 2007, Case, Quigley, and Shiller 2005). Especially house prices feature prominently in recent DSGE models including financial frictions *via* borrowing constraints (e.g. Iacoviello 2005, Iacoviello and Neri 2010). Rising asset prices raise the collateral capacity of constrained agents who can borrow and consume more (Iacoviello and Neri 2010, Campbell and Cocco 2007). Moreover, asset price movements affect financial intermediaries' balance sheets and, as a consequence of higher net worth due to a rise in asset prices, they increase their lending (Iacoviello 2010). We additionally include credit spreads, since they capture credit risk and are closely related to the external finance premium in models featuring a financial accelerator mechanism (De Graeve

³Moreover, during crisis periods, households' willingness to hold illiquid funds diminishes which reduces the availability of external funding that borrowers can draw upon (known as the "borrower's balance sheet channel") (Christiano, Motto, and Rostagno 2003). Lenders' risk aversion and greater uncertainty are additional amplifying elements during crises. See Hollo, Kremer, and Lo Duca (2012).

⁴VAR-based FCI papers which aim at assessing the importance of "financial conditions" for the macroeconomy include similar variables (e.g. Beaton, Lalonde, and Luu 2009, Goodhart and Hofmann 2001, Gauthier, Graham, and Liu 2004, Swiston 2008, Guichard and Turner 2008, Guichard, Haugh, and Turner 2009).

2008). Furthermore, credit spreads give a reasonable description of problems associated with the financial intermediation process (Gilchrist and Zakrajsek 2011). Finally, credit spreads have been shown to be useful predictors of economic activity, especially over the Global Financial Crisis (e.g. Faust, Gilchrist, Wright, and Zakrajsek 2012, Gilchrist and Zakrajsek 2012, Del Negro and Schorfheide 2013).

We identify individual financial shocks and can therefore look at the contribution of shocks to house prices, credit spreads, stock prices and the Federal Funds rate to GDP growth. Compared to time-varying parameter approaches which include aggregate measures of "financial conditions", concentrating on a few key financial variables allows us to gain a better understanding of the underlying mechanism of the overall importance of the financial sector as a source of shocks for the macroeconomy. Perhaps even more important, including individual financial variables separately also means that we do not only allow for time-varying dynamic interactions between financial and macroeconomic variables, but also explicitly between individual financial variables whereas weights of individual financial variables in the composite indexes are typically assumed constant over time. To see whether these shortcomings of using aggregate measures of "financial conditions" is outweighed by the ability of such models to account for a larger amount of information we compare the overall contribution of financial sector shocks to GDP growth estimated from our baseline TV-VAR with the contribution from a model which includes the NFCI.

3.3 Data

The model is estimated over the sample period 1958Q1 to 2012Q2 (1958Q1-1973Q1 is our training sample). The choice of this period is driven by data availability, and the sample covers several financial crises, which we will explicitly focus on further below. Financial crisis periods are defined as in Lopez-Salido and Nelson (2010) to be 1973-1975 ("Bank Capital Squeeze"), 1982-1984 ("LDC (less developed countries) Debt Crisis"), 1988-1991 ("Savings and Loan Crisis").⁵ To those dates we add the years of the two stock market crashes 1987 and 2001 and the Global Financial Crisis 2008-2009. We note that these dates encompass the economic recessions as defined by the NBER.

The vector of macroeconomic variables M_t comprises differences of the logarithms of GDP and the GDP deflator. The vector of financial variables F_t includes a house price

⁵See Lopez-Salido and Nelson (2010) for details on characteristics of the individual financial crises.

index, the S&P 500 (monthly average), the Federal Funds rate and Moody's BAA-AAA corporate bond spread.

House and stock prices are converted into real variables by division by the GDP deflator. They enter in differences of their logarithms. The Federal Funds rate and the corporate bond spread are not transformed. All series are taken from the Fred database of the Federal Reserve Bank of St. Louis, except for the house price which is taken from Robert J. Shiller's webpage and used in Shiller (2005). The series are shown in Figure 3.2 (panels (a) and (b)).

We assume that the financial variables we include capture developments in the financial sector that are most relevant for the macroeconomy, in particular during the Great Recession and the build-up of financial imbalances prior to it. We check below to what extent including additional or other variables in the model affects the main results. As the Federal Funds rate is the monetary policy instrument, we will, in the remainder of the paper, look at financial shock contributions to real economic activity including and excluding the effects of shocks to the Federal Funds rate (or monetary policy shocks).

3.4 Econometric Methodology

3.4.1 The Time-varying Parameter VAR

The analysis departs from an m -dimensional vector Y_t , which includes the macroeconomic variables M_t and the financial indicators F_t , $Y_t \equiv (M_t, F_t)'$. We assume that Y_t follows a time-varying parameter VAR(p) model:

$$Y_t = C_t + \mathcal{B}_{1t}Y_{t-1} + \dots + \mathcal{B}_{pt}Y_{t-p} + u_t, \quad E(u_t) = 0, \quad E(u_t u_t') = R_t, \quad (3.4.1)$$

$t = 1, \dots, T$, where for each t , C_t is an $m \times 1$ vector of intercepts, $\mathcal{B}_{1t}, \dots, \mathcal{B}_{pt}$ are $m \times m$ matrices of autoregressive VAR parameters and u_t denotes the $m \times 1$ vector of reduced form residuals, with $u_t \sim N(0, R_t)$. Collecting the coefficients in the $m \times (1 + mp)$ matrix $B_t' = [C_t \ \mathcal{B}_{1t} \ \dots \ \mathcal{B}_{pt}]$ and defining the $(1 + mp \times 1)$ vector $X_t = [1, Y_{t-1}', \dots, Y_{t-p}']'$, the VAR can be written more compactly as

$$Y_t = B_t' X_t + u_t. \quad (3.4.2)$$

An even more compact notation is

$$Y = X B_t + u, \quad (3.4.3)$$

where $Y = [Y_1, \dots, Y_T]'$, $X = [X_1, \dots, X_T]'$ and $u = [u_1, \dots, u_T]'$ are, respectively, $T \times m$, $T \times (1 + mp)$ and $T \times m$ matrices. The VAR order p is set to 2, following similar previous work for the US (e.g. Cogley and Sargent 2005, Benati and Surico 2008, Primiceri 2005).

We further define $b_t = \text{vec}(B_t)$, and assume that b_t evolves according to a driftless random walk:

$$b_t = b_{t-1} + \eta_t,$$

with $\eta_t \sim i.i.d. N(0, Q)$. Following standard practice, as e.g. in Cogley and Sargent (2005), we impose a stability constraint on the time-varying parameters to enforce stationarity of the system. That is, we include an indicator function that discards those draws for which the roots of the associated VAR polynomial lie inside the unit circle.

Moreover, we have:

$$u_t = A_t^{-1} H_t \epsilon_t, \quad (3.4.4)$$

where ϵ_t are structural shocks, with $\epsilon_t \sim i.i.d. N(0, I)$. The matrix A_t is lower triangular, with ones on the main diagonal and containing in the below diagonal elements the contemporaneous relations between the variables in the model. The matrix H_t is a diagonal matrix containing the reduced form stochastic volatilities of the innovations to the VAR:

$$A_t = \begin{bmatrix} 1 & 0 & \dots & 0 \\ a_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{61,t} & a_{62,t} & a_{63,t} & a_{64,t} & a_{65,t} & 1 \end{bmatrix} \quad \text{and} \quad H_t = \begin{bmatrix} h_{1,t} & 0 & \dots & 0 \\ 0 & h_{2,t} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & h_{6,t} \end{bmatrix}.$$

Both the contemporaneous relations $a_{ij,t}$ and the innovations' volatilities $h_{i,t}$ are allowed to drift over time. Following Primiceri (2005) we collect the diagonal elements of H_t in the vector $h_t = [h_{1,t}, h_{2,t}, h_{3,t}, h_{4,t}, h_{5,t}, h_{6,t}]'$, and assume that

$$\ln h_t = \ln h_{t-1} + v_t, \quad v_t \sim N(0, Z).$$

Similarly,

$$a_t = a_{t-1} + \tau_t, \quad \tau_t \sim N(0, S),$$

with a_t being constructed by row-wise stacking of the non-zero and non-one elements of the matrix A_t , namely, $a_t = [a_{21,t}, a_{31,t}, a_{32,t}, \dots, a_{65,t}]'$.

The entire system contains 4 sources of uncertainty: the innovations to the law of motion of the stochastic volatilities (v_t) and contemporaneous relations (τ_t), the innovations to the time-varying parameters b_t (η_t), and the structural shocks (ϵ_t). We assume that the vector containing all the innovations to the system is distributed according to

$$\begin{bmatrix} \epsilon_t \\ \eta_t \\ \tau_t \\ v_t \end{bmatrix} \sim N(0, V) \text{ with } V = \begin{bmatrix} I_6 & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & Z \end{bmatrix},$$

where I_6 is a 6×6 identity matrix, Q and S are positive definite matrices, and Z is a diagonal matrix. Following Primiceri (2005) we further assume that S is block diagonal, where each block corresponds to the parameters belonging to separate equations.

We estimate the model using a Markov-Chain-Monte-Carlo (MCMC) algorithm.⁶ The priors of the initial states of autoregressive coefficients, the contemporaneous correlations, the stochastic volatilities and all hyperparameters are assumed to be independently distributed. The priors for the initial states of the time-varying parameters $p(b_0)$, the stochastic contemporaneous relations $p(a_0)$ and the log of the stochastic volatilities $p(\ln h_0)$ are assumed to be normally distributed. The priors of the hyperparameters S , Q and Z are assumed to be distributed according to independent inverse-Wishart distributions. To calibrate the priors we use the corresponding OLS quantities calculated over a training sample which covers the first fifteen years of the data (60 quarters).

We compare in Figure 3.12 of the Appendix prior and posterior distributions of the hyperparameters. The posterior distributions are sufficiently different from the prior distributions indicating that there appears to be enough information in the data on the parameters. Hence, our results are not driven by the choice of the priors. To assess the convergence properties of the MCMC algorithm, we compute inefficiency factors (IF) for the draws of states from the posterior distribution. The results, presented in Figure 3.13, show that all values of the IF are well below 20, which is typically regarded as satisfactory (Primiceri 2005).

⁶Since the method is nowadays very standard we only give a brief description here and refer the reader to the excellent treatment in, among others, Cogley and Sargent (2005), Primiceri (2005) or Benati and Mumtaz (2007).

3.4.2 Shock Identification

To identify the financial shocks we carry out a Cholesky decomposition of the covariance matrix of the reduced form VAR residuals. We choose the following ordering: GDP growth \rightarrow GDP deflator inflation \rightarrow house price inflation \rightarrow credit spread \rightarrow stock price inflation \rightarrow Federal Funds rate.

By ordering the macro variables (M_t) before the financial variables (F_t) we separate macroeconomic from financial shocks. The underlying assumption is that macroeconomic variables react with a delay to financial shocks, possibly because wealth effects and effects which involve financial intermediaries take time to materialize, whereas financial variables can move instantaneously in response to macroeconomic shocks. This is a standard assumption made in structural VAR studies (see, among others, Bernanke, Boivin, and Elias 2005, Christiano, Eichenbaum, and Evans 1999, Beaton, Lalonde, and Luu 2009, Buch, Eickmeier, and Prieto forth., Eickmeier and Hofmann 2013).

Separating macroeconomic and financial shocks is all we need to do when we look at the overall contribution of financial sector shocks to growth in the next section. We will, however, then go one step further and try to better understand what shocks from the financial sector are particularly important and, if we find time variation in the contributions, try to come up with an explanation. Possible reasons are, as noted, changes in the transmission and changes in the volatility of the shocks. To tackle these issues we need to identify the individual financial shocks.

Using contemporaneous zero restrictions to identify individual financial shocks is certainly prone to critique, especially when applied to quarterly data. On the other hand, structural (DSGE) models are still not available in a form to derive meaningful and widely accepted sign restrictions which could be imposed to disentangle the various financial shocks from each other.⁷ For this reason we stick to the recursive scheme.

The consideration behind the chosen ordering within the financial block is that house prices are rather slow moving relative to interest rates, spreads and the stock price. Ordering house prices before interest rates is also in line with previous empirical work (e.g. Jarocinski and Smets 2008, Buch, Eickmeier, and Prieto forth.). Ordering the Federal Funds rate after credit spreads is consistent with Gilchrist and Zakrajsek (2012).

⁷Even for credit supply shocks, which are nowadays frequently identified with sign restrictions in empirical work, existing DSGE models would not all imply the same identifying restrictions on key variables (see Eickmeier and Ng 2011 for a discussion).

We will show below that results are reasonable. Nevertheless, we also consider below two alternative orderings for the financial variables and show that our main results are basically unaffected. We nevertheless bear in mind that the estimates only give us a first idea on the relative importance of each financial shock, while the overall contribution of the four financial shocks is better identified. A more sophisticated identification of the various financial shocks is left for future work.

3.5 Time-varying Macro-financial Linkages

3.5.1 The Overall Contribution of Financial Shocks to GDP Growth

We present in Figure 3.3 the sum of the contributions of all financial shocks (i.e. shocks to the house price, the credit spread, the stock price and the Federal Funds rate) to GDP growth together with the contribution of all (financial and macro) shocks to GDP growth.⁸ We show the median together with the 16th and 84th percentiles.

The first thing to note is that financial sector shocks, over the entire sample period, explain a large part of movements in GDP growth (panel (a)).

We observe particularly large (first positive and then negative) contributions of financial shocks at the beginning of the sample period. These large contributions are almost entirely due to shocks to the Federal Funds rate, as can be seen from panel (b) which shows the sum of the contributions of financial shocks excluding the monetary policy shocks. The large contribution of monetary policy shocks to output growth in the 1970s is confirmed by a broad literature. Benati and Goodhart (2010), e.g., argue that real interest rates in the US have been negative between 1971 and the beginning of the Volcker disinflation in October 1979, partly due to a systematic overestimation of the output gap (Orphanides 2001, Orphanides 2003). Similarly, Clarida, Gali, and Gertler (2000) attribute the Great Inflation in the 1970s to excessively accommodative monetary policy. Based on an estimated DSGE model featuring time variation in the volatility of the structural innovations, Justiniano and Primiceri (2008) show that the

⁸This is similar to studies constructing Financial Conditions Indices (FCIs) as the contribution of the sum of unexpected changes in financial variables to GDP growth over time using VARs (Beaton, Lalonde, and Luu 2009, Goodhart and Hofmann 2001, Gauthier, Graham, and Liu 2004, Swiston 2008, Guichard and Turner 2008, Guichard, Haugh, and Turner 2009). All these studies use, however, models with constant parameters. Goodhart and Hofmann (2001) or Gauthier, Graham, and Liu (2004) acknowledge that this assumption may be problematic.

variance share of GDP growth attributable to monetary policy shocks is largest around the Volcker period, consistent with our findings.

During three recessions associated with bank-related crises (i.e. the Bank Capital Squeeze at the beginning of the sample, the Savings and Loan crisis in the late-1980s/early 1990s and the Great Recession) tight financial conditions depressed economic growth. The negative financial shock contributions hit record levels during the Great Recession. Other negative financial events, such as the stock market crashes in 1987 and 2001, do not seem to have substantially affected GDP growth.

The charts also reveal positive contributions from financial shocks (other than monetary policy shocks) in the mid-1980s. However, during the last two decades positive financial shocks appear to have not, or only barely, spilled over to the real sector.

Looking at the contribution of financial shocks to growth at the end of the sample is interesting in the light of a vivid discussion in the literature and among policy makers about why the recovery after the crisis in the US has been so weak and slow. One explanation that is provided is that financial markets have not yet fully recovered from the Global Financial Crisis. This is consistent with the view that economic recoveries after financial crises are typically slow and weak (Reinhart and Rogoff 2009). Similarly, Claessens, Kose, and Terrones (2012) have shown that recoveries are weaker if they were preceded by asset price busts. A financial markets-related explanation is also consistent with Justiniano (2012), who argues that a DSGE model would require continuous adverse risk premium shocks to explain the struggling US economy. Hatzius, Hooper, Mishkin, Schoenholtz, and Watson (2010) argue that "non-classical" financial variables, such as measures of liquidity, borrower risk and the capacity and willingness of financial intermediaries to lend, failed to improve after the crisis peak. Consequently, a model, which includes these variables, would attribute the ongoing negative economic developments in the US to the financial sector, while a model, which only includes "classical" financial variables, would not. Bordo and Haubrich (2012) examine business cycle recoveries in the US since 1880 and argue that the recent recovery's weakness can be explained by negative developments in the housing sector. Those developments are probably due to households being still highly indebted and having difficulties obtaining credit.⁹

⁹See the interview by Todd Clark with Amir Sufi and C. Mayer on "Housing and the economic recovery" in summer 2012 at the Federal Reserve Bank of Cleveland. Similarly, the Federal Reserve Chairman Ben S. Bernanke identified in his speech in November 2012 at the New York Club as one of the headwinds affecting the recovery tight terms and conditions on mortgage loans, people still being unable to buy homes despite low mortgages and a substantial overhang of vacant homes.

From our financial shock contribution analysis, there is a strong rebound over the quarters after the crisis low. However, financial shocks still appear to drag GDP growth down (although the estimation uncertainty is quite large), consistent with the view that negative financial developments are, in large part, responsible for the weak recovery. We note that our model does not include "non-classical" financial variables, but instead generates this result by allowing for time variation in the dynamics of a small set of "classical" financial variables. We will show below that the weakness of the recovery can largely be attributed to negative developments in the housing market.

Taking a medium-term perspective, Figure 3.4(a) quantifies the contribution of the sum of all financial shocks to the forecast error variance of GDP growth at the 5-year horizon. The importance of financial shocks varies strongly, from around 20 percent (median estimate) between 1985 and 2005 to more than 60 percent at the beginning of the sample and about 50 percent during the Great Recession.¹⁰ The high share of variance explained in the 1970s is entirely due to large contributions of shocks to the Federal Funds rate, as shown in Figure 3.4(b) where we plot contributions of all financial shocks excluding monetary policy shocks. The variance share explained by financial shocks tends to increase around all five recession periods (based on the median estimates) and remains high 1-2 years after the recession. During the Great Recession the explanatory power of financial shocks for GDP growth variability is significantly larger than in other recessions. Overall, these findings point to significant time variation in the propagation mechanism, or in the shocks' size, or in both.

3.5.2 Contributions of Individual Financial Shocks to GDP Growth

Figure 3.5 shows the contributions of individual financial shocks to GDP growth. Several findings are worthwhile emphasizing.

First, the significantly positive contributions of all financial shocks in the mid-1980s found in Figure 3.3 are mainly due to positive credit spread shocks. An explanation is that regulatory changes in financial markets and the emergence of new financial products helped reducing financial frictions and led to expanded access to credit markets for households and firms, thereby boosting economic performance (Justiniano and Primiceri

¹⁰The share for the Great Recession is slightly smaller compared to the share explained by financial and uncertainty shocks found by Stock and Watson (forth.) of roughly 2/3. Their financial and uncertainty shocks are, however, not uncorrelated with other shocks.

2008).¹¹ Indeed, the regulatory reforms of the early-1980s mark a transition from very high and volatile to much smaller risk spreads (see Figure 3.2(b)), which our model attributes to positive credit spread shocks.

Second, the main drivers of the 2000/2001 recession were disturbances in the stock market reflecting the burst of the dot.com bubble.

Third, the boom in the mid-2000s was mainly triggered by housing shocks.

Fourth, the main financial drivers of the Great Recession were house price and credit spread shocks. House price shocks explain about 2/3 and credit spread shocks about 1/3 of the overall financial shock contributions to real economic growth over the crisis period. The large share of growth explained by house price shocks is unprecedented in our sample, and in that sense, the latest recession has been different from previous recessions. The finding is consistent with Claessens, Kose, and Terrones (2012) who show that recessions associated with house price busts tend to be longer and deeper than other recessions, which is clearly the case for the Great Recession. The relatively large part explained by credit spread shocks is in line with Gilchrist and Zakrajsek (2012).

Fifth, since the end of 2008, there are basically no contributions of shocks to the Federal Funds rate, which is potentially due to the zero lower bound of nominal interest rates the Federal Reserve hit at the end of 2008. Unconventional monetary policy measures launched in 2009/2010 are probably captured by credit spread shocks which made large positive contributions around this time. Indeed, Krishnamurthy and Vissing-Jorgensen (2011) show, using an event study approach and a regression analysis, that QE1 has substantially reduced corporate bond spreads. Moreover, at the end of the sample, our model suggests that house price shocks still drag GDP growth down, which explains the overall negative contributions of financial shocks found in Figure 3.3. This finding is in line with Claessens and Kose (2013) who show for a large number of countries that the economy typically starts recovering from recessions before house prices have bottomed out.

In Figure 3.6 we present the time-varying forecast error variance shares of GDP growth explained by each financial shock. The explanatory power of house price shocks soured during the last 15 years, from below 5 percent to about 40 percent of the variation in GDP growth in the years after the Global Financial Crisis. Although the uncertainty

¹¹One example is the passing of the Depository Institutions Deregulation and Monetary Control Act (DIDMCA) in 1980. The DIDMCA increased deposit insurance from \$40,000 to \$100,000 and established the complete phase-out of interest rate ceilings on deposits, known as Regulation Q. Another example is the securitization of mortgage loans, which picked up pace in the early-1980s (Estrella 2002).

surrounding these estimates is relatively large, the variance share explained by the house price shock in the most recent years exceeds significantly that in previous decades.¹² Credit spread shocks are quite important during recession periods with largest values of about 20 percent in the first two and the last recessions of the sample. The variance shares explained by credit spread shocks are quite precisely estimated. Accordingly, the importance of credit spread shocks is significantly larger during most recessions than during boom periods. Variance shares explained by stock price shocks are relatively high around the two major stock market crashes in our sample (1987 and 2001) and during the build-up of the dot.com bubble in the 1990s. In these periods the explanatory power of stock price shocks is at roughly 10 percent compared to virtually nothing in other times. During the recent financial crisis, the stock market seems to have played basically no role. We have already commented on the high variance share explained by shocks to the Federal Funds rate at the beginning of the sample. Much smaller peaks are, again, visible around 2001 and 2008/2009. These latter peaks are consistent with the view that the Federal Reserve pursued a "mop up" strategy after the burst of the stock price and the housing and credit bubbles, respectively, which has become a consensus on what central banks should do in response to negative financial market developments (e.g. Issing 2009). In general, the contribution of monetary policy shocks has been very low in the last two decades, consistent with other structural VAR (or FAVAR) studies (e.g. Jarocinski and Smets 2008, Eickmeier and Hofmann 2013).

3.5.3 Stochastic Volatility or Changing Dynamics?

So far, our analysis has shown non-negligible time variation in the relation between the financial sector as a whole and the real economy, but also between specific key segments of the financial sector and the real economy. In the following we will proceed to analyze whether we can attribute the revealed time variation to changes in the size of financial shocks or to changes in the transmission mechanism of financial shocks to GDP growth or to both.

¹²The average forecast error variance shares explained by house price shocks before the Global Financial Crisis are broadly in line with those of Jarocinski and Smets (2008). They find housing demand shocks to explain between 6 and 10 percent in the medium run. Their estimates are based on a constant parameter VAR estimated over 1987-2007.

Shock Volatilities

We start by presenting in Figure 3.7 the time-varying standard deviations of the orthogonalized financial shocks. There is a substantial and significant amount of time variation. Moreover, it is striking how similar Figures 3.6 and 3.7 are in shapes. This suggests that much of the time variation in the variance decomposition of GDP growth is due to changing shock volatilities. This finding is in line with basically all previous time series studies reviewed in Section 2, and strongly supports our strategy to take time variation in the shock volatilities into account. We note, in addition, that, although we have used a recursive identification scheme, our estimated volatility of the shocks to the Federal Funds rate is remarkably similar to the one obtained by Justiniano and Primiceri (2008) from an estimated DSGE model.

The Role of Changing Dynamics

In Figure 3.8 we present median impulse responses of GDP growth to unit financial shocks obtained from the TV-VAR for horizons up to 5 years and all points in time. The impulse responses are constructed such that the initial shock is of the same size, i.e. the impact effect on asset prices, credit spreads and the Federal Funds rate is 1 percent and 1 percentage point, respectively, at each point in time. This allows us to isolate changes in the transmission from changes in the size of the shocks.

Signs and shapes of the impulse responses look reasonable. Unexpected increases of house prices and stock prices have positive temporary effects on GDP growth. The effects of stock price and credit spread shocks on GDP growth are more short lived than those of other financial (especially house price) shocks. The relatively persistent output growth effects of house price shocks might be explained by wealth effects being larger for housing wealth than for financial wealth as found, e.g., by Case, Quigley, and Shiller (2005), Case, Quigley, and Shiller (2013) and Carroll, Otsuka, and Slacalek (2011). Positive shocks to the Federal Funds rate (reflecting a monetary policy tightening), by contrast, lead to temporarily contractionary real effects.

Conceptually in line with Gali and Gambetti (2009), we plot in Figure 3.9 impulse responses averaged over selected periods of time, and in Figure 3.10 we show differences between these periods.¹³ We first compare in panels (a) financial crises, as defined in

¹³Specifically, for each draw from the Gibbs Sampler, we average the impulse responses over each of the selected periods, and then compute the quantiles over the draws. Similar, for the differences

the data section, and non-crisis periods to evaluate asymmetries in the transmission of financial shocks over the financial cycle. Panels (a) of Figures 3.9 and 3.10 suggest that during the two stock market crashes and the 1988-1991 crisis, the transmission of the financial shocks did not differ significantly from the transmission in normal times. By contrast, we find significant differences in the propagation of all shocks but house price shocks in the 1973-1975 crisis, of credit spread shocks in the 1982-1984 crisis, and of credit spread and house price shocks in the Global Financial Crisis. Hence, there seem to be differences in the transmission in normal periods compared to periods of financial turbulence. These differences, however, are not systematic in terms of significance and sign across crisis periods. Over the Global Financial Crisis period, the real effects of credit spread and house price shocks have, however, clearly been stronger than in normal times, which could be due to the specific nature of the latest crisis or to monetary policy having hit the zero lower bound and having undertaken unconventional measures.¹⁴

In panels (b) of Figures 3.9 and 3.10 we provide impulse responses and differences between them for each decade (the 1970s until the 2000s) averaged only over non-crisis years to test for gradual changes in the transmission. The real short-term effects of house price shocks are significantly lower in the 1990s and the 2000s compared to the two previous decades. At the same time though, the effects of house price shocks became more persistent between the beginning of the sample and the last decade. As can be seen from Figure 3.8, the impact of house price shocks on GDP growth gradually decreased over the last two decades, potentially due to the increasing usage of mortgage securitization making the economy more resilient to house price shocks. However, starting at the end of the 1990s until the beginning of the disruptions in the housing market, the impact of the house price shock on GDP growth continuously increased to levels seen in the 1980s. This finding is not surprising given that housing wealth relative to GDP has strongly increased from 1.5 in the mid-1990s to 2.3 in 2005 (Iacoviello 2010). Another reason for the increased effect of housing shocks on output growth in the second half of the 2000s could be that an increase in house prices may have been triggered by the extension of subprime mortgage lending (which may have been picked up by our house price shock)

between the selected periods, again for each draw from the Gibbs Sampler, we average the impulse responses over each of the periods, take the difference between the averages of the selected periods, and then calculate the quantiles over the draws.

¹⁴We can also not exclude that our finding is due to the simple fact that the duration of the Global Financial Crisis has been longer than that of previous crises and that our model, which allows for smoothly time-varying parameters, can only detect those parameter changes that occur for sustained periods of time.

which allowed households to borrow at easy terms in order to buy houses (e.g. Mian and Sufi 2009). Moreover, financial intermediaries could increase their lending as a consequence of higher net worth due to rising house prices. The decline in house prices since 2006 then led to a reversal of these developments with similar (negative) effects on GDP growth. These explanations are in line with Iacoviello and Neri (2010) who argue that housing preference shocks have larger effects on GDP when collateral effects are taken into account.¹⁵ They are also consistent with Eickmeier and Hofmann (2013) who emphasize the high comovement of house prices and (mortgage and other) credit in a time series model for the US. We finally note that the time-varying pattern we obtain for house price shocks is in line with Case, Quigley, and Shiller (2013) who find larger housing wealth effects between 1975 and 2012 than between 1982 and 1999.

The short-term (negative) effects of credit spread shocks remained unchanged. The effects of stock price shocks have become significantly larger in the 1990s and 2000s compared to the 1970s and the 1980s, consistent with financial wealth having become more important over the course of the stock market rallies in the 1990s. Finally, we find that the negative effects of policy interest rate shocks on growth have weakened over time, in line with much of the previous empirical literature (see the overview of this literature in Table 4 of Eickmeier, Lemke, and Marcellino (2011a)). We find a short-run output puzzle (as well as a price puzzle (not shown in the paper)) at the beginning of the sample which then disappears. This is consistent with the notion that the Federal Reserve violated the Taylor principle before the era of Paul Volcker as a chairman (Clarida, Gali, and Gertler 2000) and with the TV-VAR evidence by Korobilis (2012).

Finally, in order to better understand the underlying sources of the time variation in the impulse responses we show in Figure 3.14 in the Appendix the evolution of the autoregressive parameters (i.e. the elements of B_t summed over the two lags) and of the contemporaneous relations associated with the financial shocks (i.e. the corresponding

¹⁵They estimate their DSGE model with a housing market over two sample periods, 1965-1982 and 1999-2006. They argue that financial reforms led to several developments in the credit market which enhanced the ability of households to borrow and thereby reduced the fraction of credit constraint households. They find that the effects of housing preference shocks on economic activity have increased between the two samples. These results are not directly comparable to ours, because they have included years prior to the 1970s in their first subsample and they look at a housing preference shock (whereas we look at a more broadly defined shock to the house price) and at effects on the components of GDP, not GDP. They find that short-run responses of residential and business investment have declined, but that responses have become more persistent over time, which is what we find for GDP. By contrast, they find the opposite for consumption.

elements of A_t). There is time-variation in both autoregressive and contemporaneous relations. Time variation in the off-diagonal elements of the covariance matrix is more significant than in the autoregressive parameters.

Overall, our results suggest significant changes in the transmission of financial shocks to the real economy over time, which supports our strategy of not only accounting for time variation in the shock volatility but also in the autoregressive and the contemporaneous correlation parameters. This finding is quite new. Most previous time series studies featuring time-varying parameters do not find evidence for time variation in the transmission.¹⁶

3.6 Alternative Models and Robustness Analysis

In this section we compare the main outcomes of our baseline TV-VAR with the results from a constant parameter VAR (C-VAR), and from a TV-VAR in which we replace house and stock price inflation and the credit spread by the NFCI. We also check for robustness with respect to the ordering of financial variables for shock identification, and to the inclusion of the growth rate of the volume of credit or of the oil prices in our baseline model.

3.6.1 Comparison with a C-VAR

The C-VAR contains the same variables as the TV-VAR and is estimated over the same sample period.¹⁷ ¹⁸ Figure 3.11 shows the overall contributions of financial sector shocks while Figure 3.12 presents the contributions of financial sector shocks excluding monetary

¹⁶It is worth noting that Benati and Surico (2008) demonstrate that changes in the structural monetary policy rule may well be identified as changes in the shock variances in TV-VARs (see also Benati and Goodhart 2010 for a discussion of this issue). In this light, our finding of significant time variation in the propagation mechanism is even more striking.

¹⁷We estimate the constant parameter VAR using Bayesian methods, assuming an independent Normal-Wishart prior along the lines of Koop and Korobilis (2010). To calibrate the prior hyperparameters in this exercise we use the corresponding OLS quantities estimated over a training sample of 60 quarters. Our choice to use this specific prior distribution, and to calibrate the prior hyperparameters using a training sample of this specific length, is motivated by the desire to keep the C-VAR conceptually as close as possible to the TV-VAR.

¹⁸Given the well known structural breaks associated with the conduct of monetary policy in the late 1970s/early 1980s, we have also estimated the C-VAR starting in 1985. Since impulse responses and historical decomposition results are very similar for the two C-VARs after 1985 we present only results from the C-VAR estimated over the entire sample period.

policy shocks. Panel (a) plots GDP growth (black line) together with the median overall contributions estimated from the benchmark TV-VAR (red line), and the C-VAR (green line). Panel (b) of Figure 3.11 presents the median overall contributions implied by the C-VAR alongside the 16th and 84th percentiles.

The contributions estimated from the C-VAR and the TV-VAR are, over most of the sample period, remarkably similar. Indeed, during the second half of the 1980s and throughout the 1990s the two series nearly coincide.

We observe notable differences over mainly three periods: 1975-1980, 2002-2006 and the post-crisis period. During 1975-1980, the contribution of financial shocks implied by the TV-VAR is first larger, and then smaller than the contribution implied by the C-VAR. The differences are entirely due to large shocks to the Federal Funds rate found in the TV-VAR, but not in the C-VAR. Over the 2002-2006 period, the financial sector shock contributions implied by the C-VAR exceed those implied by the TV-VAR. Hence, over this boom period, the C-VAR seems to attribute a larger fraction of GDP growth to financial shocks than the TV-VAR. This points towards asymmetries in the transmission mechanism of financial shocks to the real economy, which the C-VAR, in contrast to the TV-VAR, is unable to capture. Since mid-2009 the contributions of financial shocks estimated from the C-VAR are significantly positive. They turn negative again only at the very end of the sample period. This confirms that time variation in the parameters of our baseline model is needed to attribute the weak economic recovery to negative financial sector developments.

In the Appendix (Figures 3.15 and 3.16) we show results for individual financial shocks obtained from the C-VAR. House price shocks make relatively strong positive contributions in the mid-2000s, which the TV-VAR does not find. The result from our baseline TV-VAR is in line with Guerrieri and Iacoviello (2012) who find that negative house price shocks, leading to borrowing constraints becoming binding, have larger (negative) effects on economic activity than positive house price shocks which lead to a relaxation of collateral constraints. It is also in line with Case, Quigley, and Shiller (2013) who find that positive housing wealth effects from house price increases are significantly smaller than negative ones from house price declines.¹⁹ We finally note that impulse response functions obtained from the C-VAR are very similar to those obtained from the TV-VAR averaged over the entire sample period (see Figure 3.15 in the Appendix).

¹⁹Case, Quigley, and Shiller 2013 argue that "painful regret due to loss of home value has different psychological consequences than does the pleasant elation due to increase in home value, which frees up new opportunities to consume home equity." See also Genesove and Mayer (2001).

3.6.2 Comparison with a TV-VAR that includes a Financial Conditions Index

As another exercise we assess the benefit of exploiting lots of financial time series when examining financial sector shock contributions. For that purpose we replace house price inflation, stock price inflation and credit spreads with the NFCI published by the Federal Reserve Bank of Chicago (see Figure 3.2 (c)). The NFCI is constructed as the first latent factor extracted from an unbalanced panel of 100 financial indicators, covering money markets, debt and equity markets and the banking system.²⁰ Importantly, the NFCI also captures "non-classical" financial segments. For details on the series and the construction of the index, see Brave and Butters (2011).

Although the Federal Funds rate enters the large dataset (as deviations from overnight repo rates) from which the NFCI is constructed we still include it as an additional variable in the TV-VAR. This helps us to disentangle monetary policy from other financial shocks. Consistent with the identification scheme used in our baseline model we order the NFCI before the Federal Funds rate and behind GDP growth and GDP deflator inflation. The NFCI is only published since 1973. We therefore estimate the model over 1973-2012 and use 1973-1984 as our training sample.²¹²²

Panels (a) and (c) of Figure 3.11 show the sum of the contributions of all financial sector shocks to GDP growth (i.e. shocks to the NFCI and the Federal Funds rate), and panels (a) and (c) of Figure 3.12 show the contributions of all financial sector shocks excluding shocks to the Federal Funds rate (i.e. only shocks to the NFCI). The evolution of the financial sector shock contributions from the baseline TV-VAR and the TV-VAR which includes the NFCI are quite similar. The NFCI model suggests slightly less negative financial shock contributions over recession periods, but tracks the Great Recession also fairly well. Moreover, no significant positive contributions of financial shocks to GDP growth are found, which is similar to the finding from the baseline TV-

²⁰The set comprises indicators covering interest rate spreads, implied volatility and trading volumes, equity and bond price measures (capturing volatility and risk premiums, real estate prices, asset-backed security), survey-based measures of credit availability as well as accounting-based measures for commercial banks and shadow banks.

²¹For comparability, we re-estimated the baseline TV-VAR also over this shorter sample period, but results for 1985-2012 from that model remain very similar to those from the baseline TV-VAR estimated over the long sample period.

²²The Federal Reserve Bank of Chicago also publishes an adjusted NFCI (which is the NFCI after removal of macroeconomic influences). We use the unadjusted FCI because macroeconomic influences are already taken care of in the VAR.

VAR since the 1990s. In contrast to the baseline results, the NFCI model suggests that financial shocks have contributed negatively in the late-1980s. This is probably because stock market developments are given a relatively large, time-constant weight in the NFCI: the second largest negative loading is associated with the S&P 500 index, and the 12th largest positive loading with stock market volatility (see Table A1 in Brave and Butters 2011). By contrast, Figure 3.5 (obtained from our baseline model) shows that negative contributions from the stock market during this period are fully compensated by positive contributions from other financial shocks, and especially shocks to credit spreads.

A final point worthwhile stressing is that, although the NFCI itself points towards above average financial developments over the post-2008/2009 recession period (see panel (c) in Figure 1), the contributions of shocks to the NFCI to GDP growth are negative over this period confirming the finding from our baseline model. As an additional check we re-estimate a constant parameter VAR with GDP growth, inflation, the NFCI and the Federal Funds rate. We find that financial conditions, again, make strong negative contributions at the end of the sample similar to the ones obtained from our baseline TV-VAR and the alternative TV-VAR presented in this section. Hence, negative financial shock contributions after the Great Recession can be detected either by considering a large number of financial variables including "non-classical" ones, in line with Hatzius, Hooper, Mishkin, Schoenholtz, and Watson (2010), or by allowing for time variation in the parameters in a VAR with a few standard key financial variables.

3.6.3 Further Robustness Checks

Changing the ordering of the variables for shock identification In this section we carry out several robustness checks. First, we consider two alternative orderings for the financial variables in the baseline TV-VAR. One is: house price inflation \rightarrow Federal Funds rate \rightarrow credit spread \rightarrow stock price inflation. This ordering implies that the Federal Funds rate responds with a delay to shocks to credit spreads and the stock market, which may be seen as a plausible assumption, given that monetary policy decisions are typically taken every six weeks (Swiston 2008). The other ordering we consider is: house price inflation \rightarrow stock price inflation \rightarrow credit spread \rightarrow Federal Funds rate, i.e. we switch the ordering between stock price inflation and the credit spread.

Figures 3.17-3.24 in the Appendix show that our main results are basically unaffected. The only difference which is worthwhile mentioning is that when we switch the ordering between credit spreads and stock price inflation, stock price shocks replace credit spread shocks as second largest financial contributor to the Great Recession (Figure 3.21). This is not surprising given the high negative correlation between stock price inflation and credit spreads (and between the residuals of the corresponding equations) over the past few years (Figures 3.2(b) and 3.14(b)). On the one hand, the time-varying volatility of stock price shocks looks less plausible with this alternative ordering compared to the baseline ordering (Figure 3.23). Peaks are not anymore visible around the stock market crashes. On the other hand, stock market wealth has dropped by 50 percent between 2007Q3 and 2009Q1 (see Hubrich and Tetlow 2012) so that negative stock market wealth effects cannot be excluded. We leave it for future research to adopt a more sophisticated identification scheme to better disentangle stock price and credit spread shocks.

Including credit in the model As another robustness check, we introduce real total credit growth, taken from the Federal Reserve’s Flow of Funds Accounts, in our baseline TV-VAR.²³ This is in order to assess whether the main results obtained so far are influenced by the fact that we omit a measure of the volume of credit and only use credit spreads to capture the credit market. One could argue that only a physical cut-back in credit supply has major effects on the economy.²⁴ We order credit growth after house price inflation and before credit spreads and otherwise adopt the same ordering as in the baseline model. Hence, the sum of the contributions of credit growth and credit spread shocks can be seen as the overall contribution from the credit market. Detailed results are available upon request, here we only summarize the main findings.

The overall contribution of financial shocks (which now includes the contribution of credit growth shocks) is almost identical to the baseline one. Thus, in the baseline model, other shocks seem to have picked up credit growth shock contributions. There is not much time variation in the transmission or in the volatility of the shocks, and the contribution of credit growth shocks to the forecast error variance of GDP growth is very small, never exceeding 5 percent (median estimate), with the exception of peaks in the

²³Using business credit or corporate bonds, which are even more closely linked to the corporate bond spreads, instead of total credit yields very similar results.

²⁴Helbling, Huidrom, Kose, and Otrok (2011), for example, argue that it is important to take into account the volume of credit to assess the role of credit supply shocks.

transmission and variance contribution around the S&L crisis and around the housing and credit boom in the mid-2000s.

Including the oil price in the model As a final check on the robustness of our findings, we include the growth rate of the real price of oil in our baseline model. It has been argued that the large increase in oil prices in the run-up to the Global Financial Crisis has been one contributor to the subsequent strong downturn in economic activity (Hamilton 2009) and the increase in economic volatility (Clark 2009). We wish to test whether including the oil price reduces the contribution of financial shocks over that period or whether other variables have instead already captured exogenous oil price fluctuations. Again, detailed results are available upon request.

We use as a measure of the oil price the US refiners' acquisition cost for imported crude oil, as reported by the Energy Information Administration. That measure is available from 1974Q1 onwards, and we backdate it using the US producer price index of crude oil. We deflate the oil price by the US consumer price index. We order oil price inflation in the macroeconomic block, as previous studies have shown that most of the oil price movements are due to global demand shocks (Hamilton 2009, Kilian 2009). We do not attempt to formerly identify specific types of oil shocks, since this is not the focus here.

Our main results are basically unaffected by this change to the model. Most importantly, the contribution of financial shocks over the Great Recession period is not diminished by the inclusion of the oil price. Hence, shocks to GDP growth and inflation have captured oil price shocks in our baseline model.

3.7 Conclusions

We have analyzed the macro-financial linkages in the US based on a Bayesian VAR with time-varying parameters estimated over 1958-2012. The model includes GDP growth and inflation as well as a few key financial indicators (credit spreads, the Federal Funds rate, house and stock prices). It has thus two important features which many of the standard macro models used in academic research and central banks are, so far, still lacking: financial variables and time variation in the relationship between the macroeconomy and the financial sector. We have examined the contributions of financial shocks to GDP growth and shed light on possible changes in the volatility of financial shocks and

their impact on GDP growth. We have also compared the outcome of the time-varying parameter model with that of a constant parameter VAR and a time-varying parameter VAR where the financial indicators are replaced with the Fed of Chicago's NFCI.

Our main findings are: (i) Over the Great Recession period, the explanatory power of financial shocks for GDP growth rose to roughly 50 percent, compared to 20 percent in normal times. House price shocks were very important in explaining the Great Recession, accounting for about 2/3 of the overall contribution of the financial sector to GDP growth. The size of house price and credit spread shocks has been larger and the transmission to growth stronger than previously.

(ii) The slow and weak recovery from the Global Financial Crisis is due to negative developments in the housing market, probably due to households being still credit constrained. The C-VAR does not generate negative financial shock contributions at the end of the sample period. However, a constant parameter model which includes the Fed of Chicago's NFCI, does. This suggests that a model which includes a large number of financial variables can also capture the complex dynamic interactions of financial markets and the macroeconomy, which we pick up by our time-varying parameter model.

(iii) As concerns the pre-Global Financial Crisis period, we detect significantly positive contributions of credit spread shocks to GDP growth in the mid-1980s, reflecting the process of financial deregulation. Moreover, we find significantly negative financial shock contributions around two other banking crises, the Bank Capital Squeeze in the early-1970s and the Savings and Loan crisis in the late-1980s/early-1990s, due to particularly large credit spread shocks and credit spread and housing shocks, respectively. Other financial events, such as the stock market crashes in 1987 and 2001, did not have significantly negative real effects.

(iv) Finally, the housing sector affects the macroeconomy asymmetrically, with negative shocks being more important for the macroeconomy than positive shocks. Moreover, we find a trend increase in the transmission and in the size of housing shocks since the early-2000s, probably due to a rise in housing wealth and extended mortgage lending.

3.8 References

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3.9 Figures

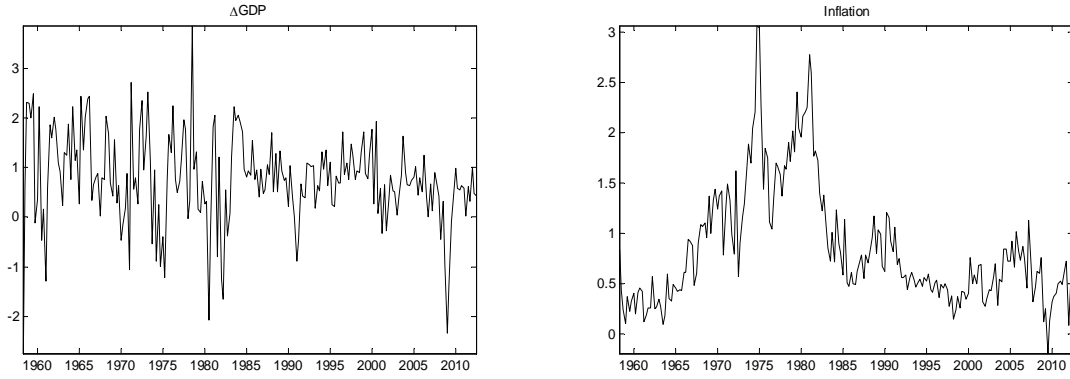
Figure 3.1: Overview of Empirical Literature on Time-varying Macro-financial Linkages

Study	Model	Varying params	Time variation	Financial shocks	Identification	Period	Country/ies	Results
Balke (2000)	VAR (4 variables)	Coefficients	Threshold	Credit	GIRFs	1960-1997	US	Stronger impact in low credit growth regime.
Calza/Sousa (2006)	VAR (4 variables)	Coefficients	Threshold	Credit	GIRFs	1981-2002	EA	Stronger impact in low credit growth regime.
Hollo et al. (2012)	VAR (2 variables)	Coefficients, shock vola	Threshold	Systemic financial stress indicator	Recursive	1987-2011	EA	Shock size bigger in stress periods, transmission only in stress periods.
Davig/Hakkio (2010)	VAR (2 variables)	Coefficients, shock vola	Markov switching	Financial stress index	Recursive	1990-2010	US	Stronger and more persistent real effect and larger shock size in distressed compared to normal regime.
Kaufmann/Valderrama (2010)	VAR (5 variables)	Coefficients, shock vola	Markov switching	Credit, equity price	GIRFs	1980-2004	US, EA	Changes in the shock size and transmission.
Hubrich/Tetlow (2012)	VAR (5 variables)	Coefficients, shock vola	Markov switching	Financial stress index	Recursive	1988-2011	US	Shock volatility and coefficients change. The shock size is bigger in financial stress periods.
Nason/Tallman (2012)	VAR (7 variables)	Shock vola	Markov switching	Credit supply and demand	Recursive	1890-2010	US	Changes in shock vola, financial crisis regime (which includes the major wars).
Guerrieri/Iacoviello (2012)	VAR (2 variables)	Coefficients	Dummy variable approach	House price	Recursive	1975-2011	US	Decreases in house prices affect consumption more than increases.
Eickmeier et al. (2011)	FAVAR (10 latent and observed factors)	Coefficients, shock vola	Smooth	US financial conditions index	Recursive	1971-2009	9 advanced countries	Gradual increase of the transmission over time, shock size bigger in financial crises.
Gambetti/Musso (2012)	VAR (5 variables)	Coefficients, shock vola	Smooth	Credit supply	Sign restrictions	1980-2010	US, UK, EA	Changes in shock volas, increases in the transmission in recent years.
Ciccarelli et al. (2012)	Panel VAR (7 variables per country)	Coefficients	Smooth	US and Spanish stock price, Swedish credit	GIRFs	1980-2011	10 advanced countries	No changes in the transmission.

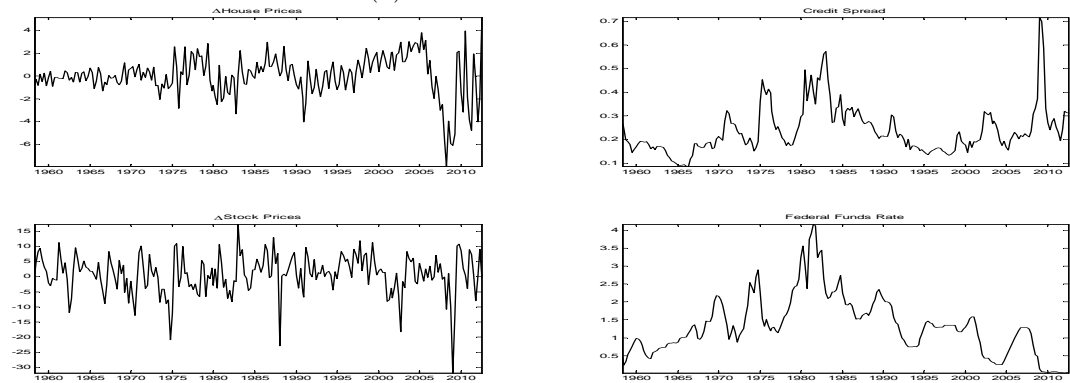
Notes: In the VAR applications, which look at shocks to a financial conditions or a financial stress index, the index is counted as one variable. The indexes are, however, typically formed of a large number of financial variables.

Figure 3.2: Time Series Plots

(a) Macroeconomic series



(b) Observable financial series



(b) NFCI from the Federal Reserve Bank of Chicago

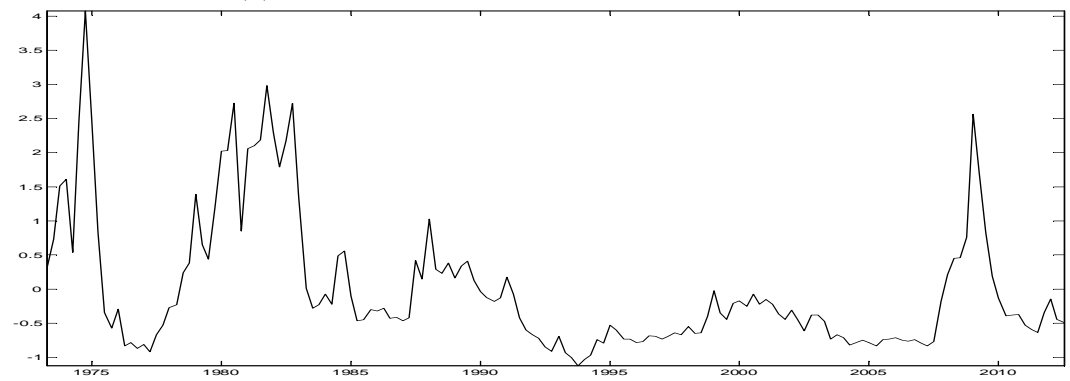


Figure 3.3: Overall contribution of financial shocks estimated from the TV-VAR (median and 1 standard deviation percentiles)



Notes: Historical contributions are computed for period 0 as the shock estimate at period 0 times the contemporaneous impulse response function (IRFs), for period 1 as the shock estimate at period 0 times the IRF at horizon 1 plus the shock estimate at period 1 times the contemporaneous IRF etc. Thus, the forecast horizon is 0 for the first observation, 1 for the second, ... and T-1 for the last observation. Red lines: historical contribution of financial sector shocks and 16th and 84th percentiles. Black line: contribution of all shocks (which broadly corresponds to deviations of GDP growth from its deterministic component). Grey shaded areas indicate recession dates according to the NBER recession dating committee.

Figure 3.4: Forecast error variance shares at the 5-year horizon of GDP growth explained by shocks to all financial variables (median estimates and 1 standard deviation percentiles)

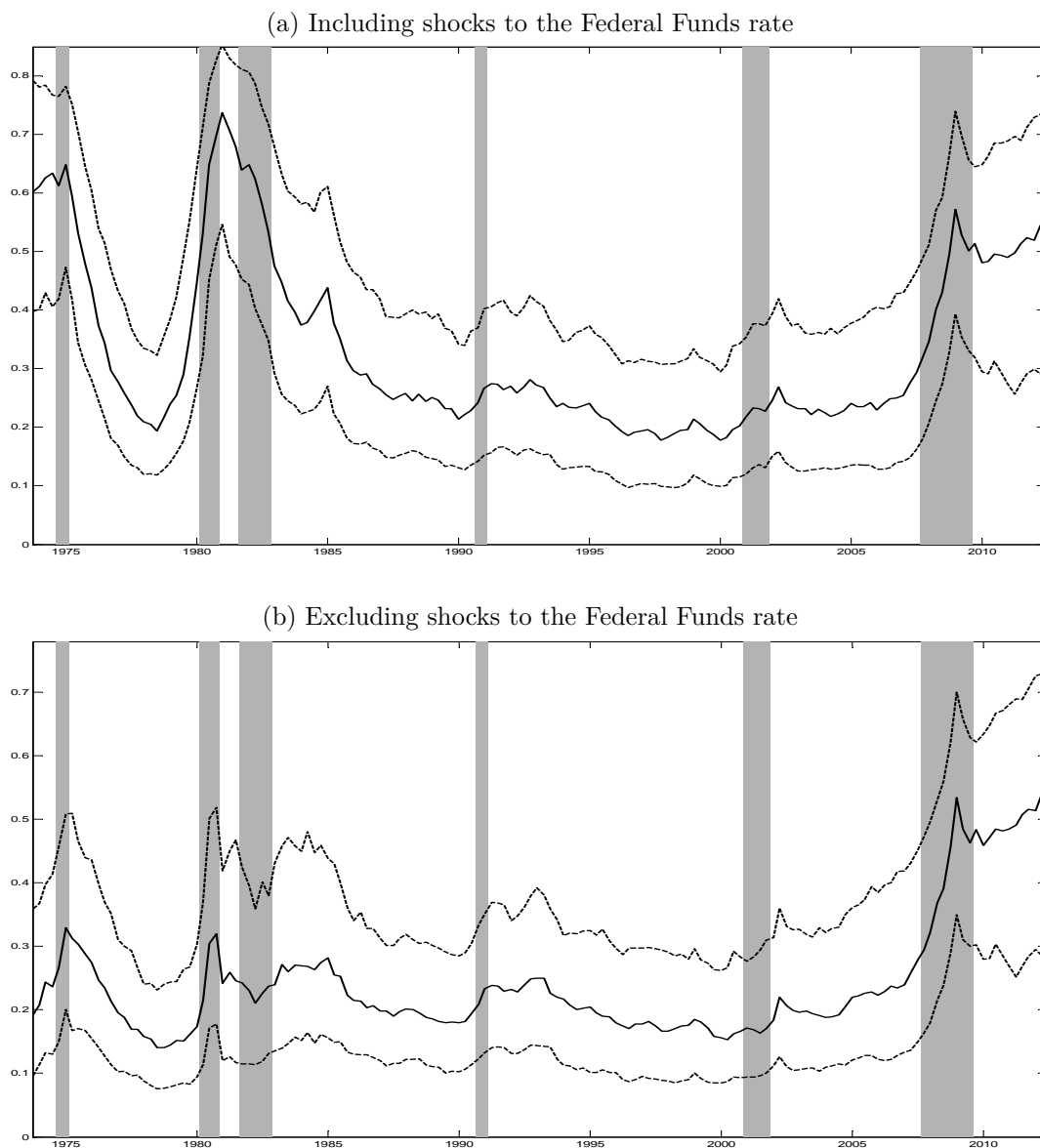
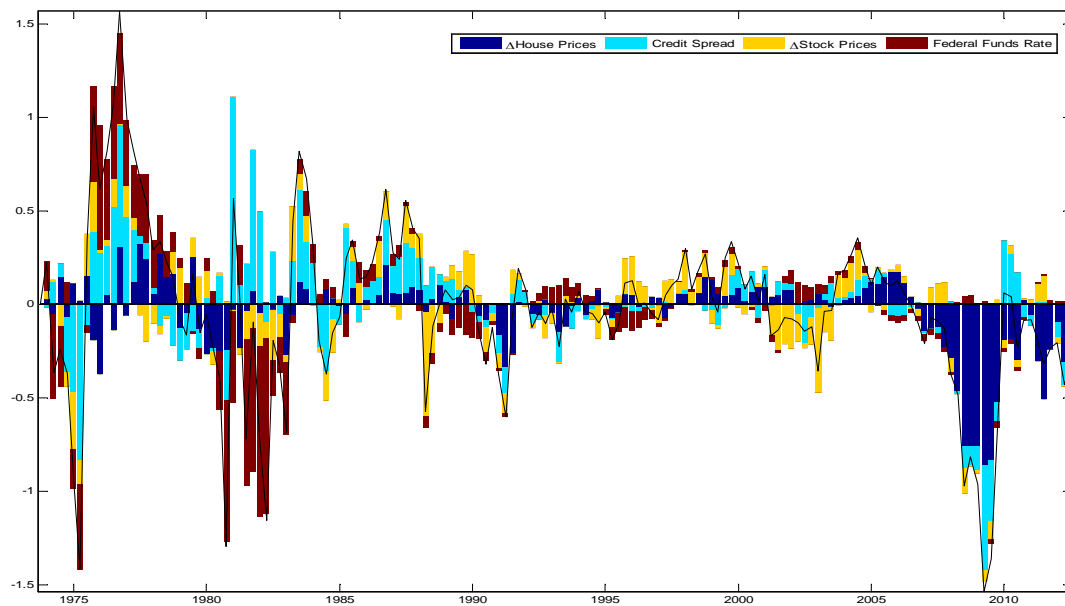


Figure 3.5: Contributions of individual financial shocks estimated from the TV-VAR (median estimates)



Notes: See Figure 2

Figure 3.6: Forecast error variance shares of GDP growth at the 5-year horizon explained by individual financial shocks estimated from the TV-VAR (median estimates and 1 standard deviation percentiles)

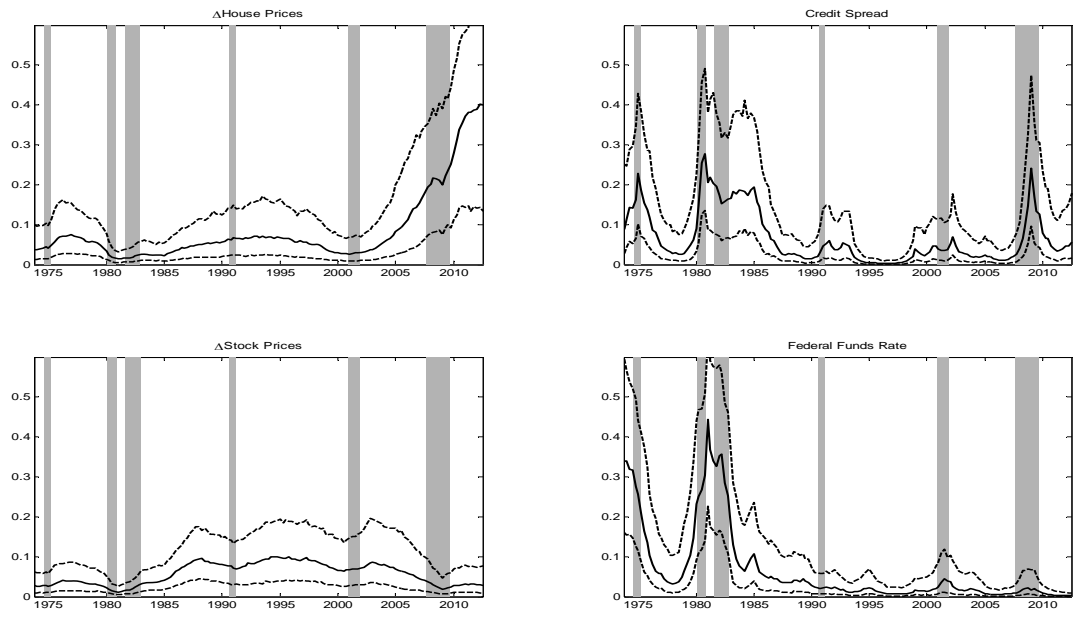


Figure 3.7: Standard deviations of structural shocks estimated from the TV-VAR (median estimates and 1 standard deviation percentiles)

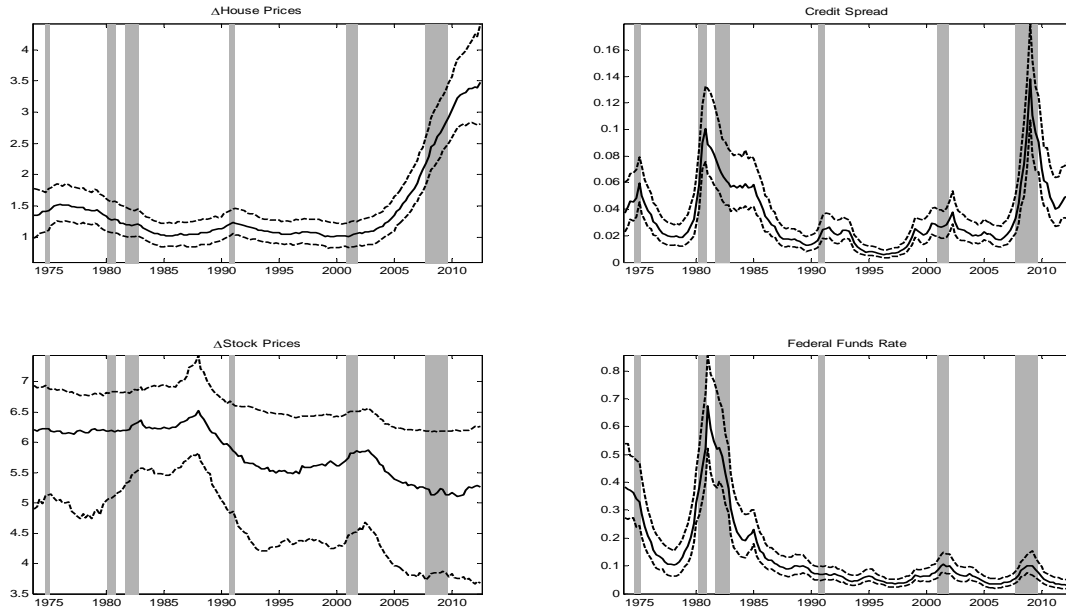


Figure 3.8: Impulse responses of GDP growth to unit financial shocks estimated from the TV-VAR (median estimates)

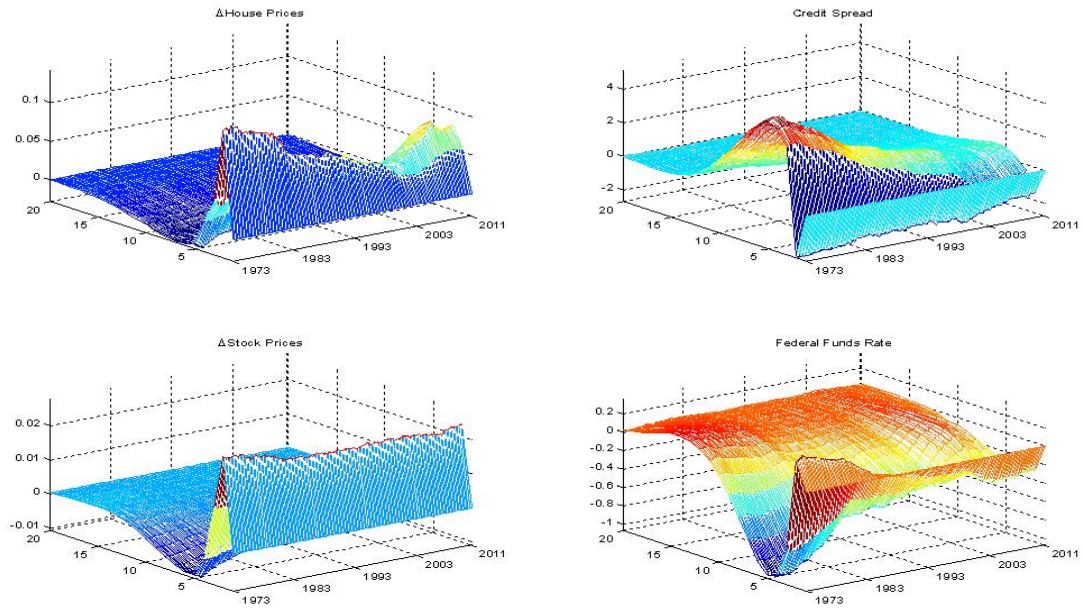


Figure 3.9: Impulse responses of GDP growth to unit financial shocks estimated from the TV-VAR on average over selected periods (median estimates and 1 standard deviation percentiles)

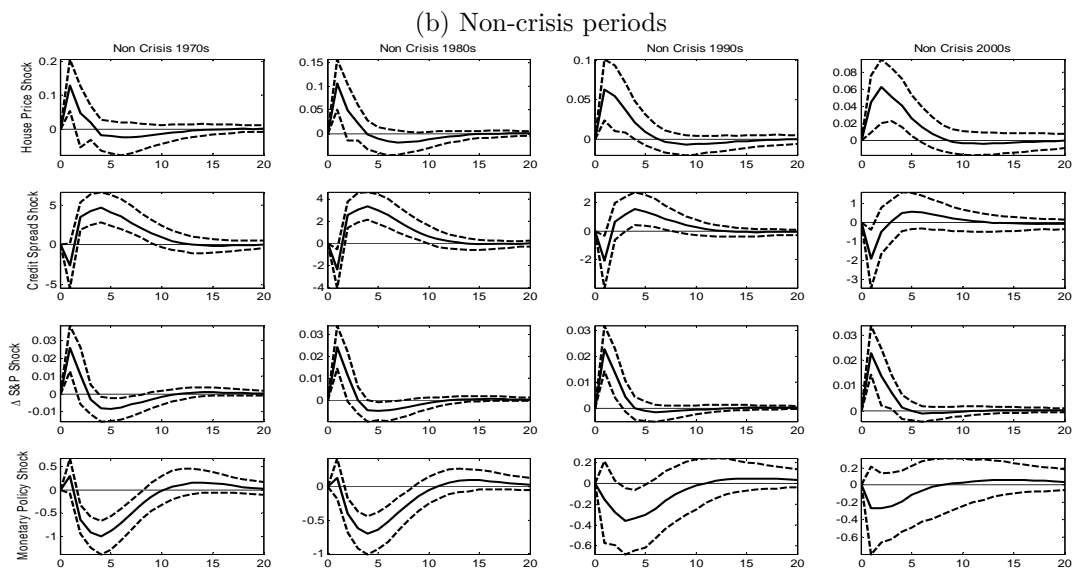
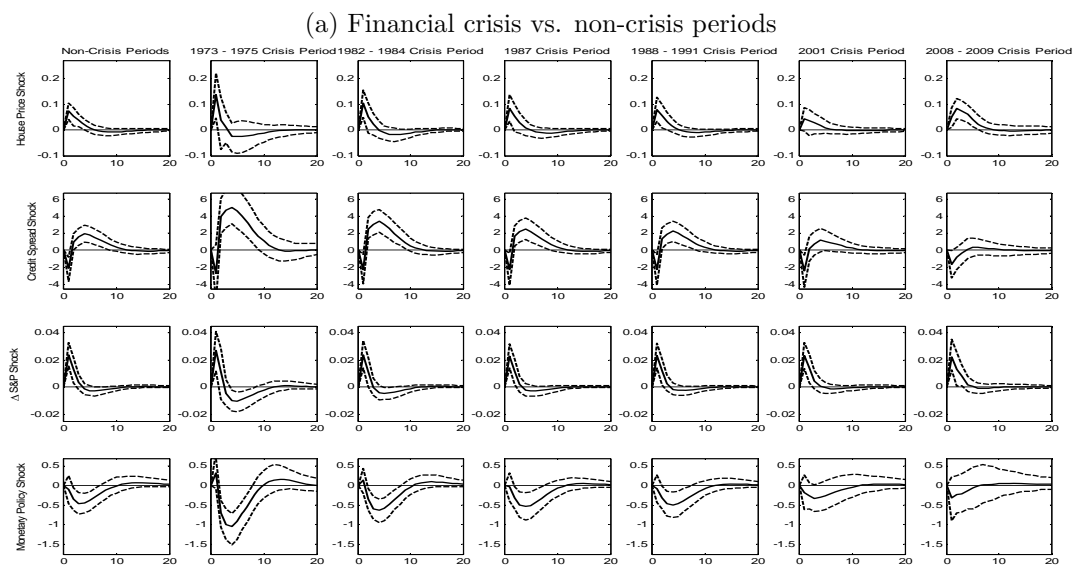


Figure 3.10: Differences of impulse responses of GDP growth to unit financial shocks estimated from the TV-VAR on average over selected periods (median estimates and 1 standard deviation percentiles)

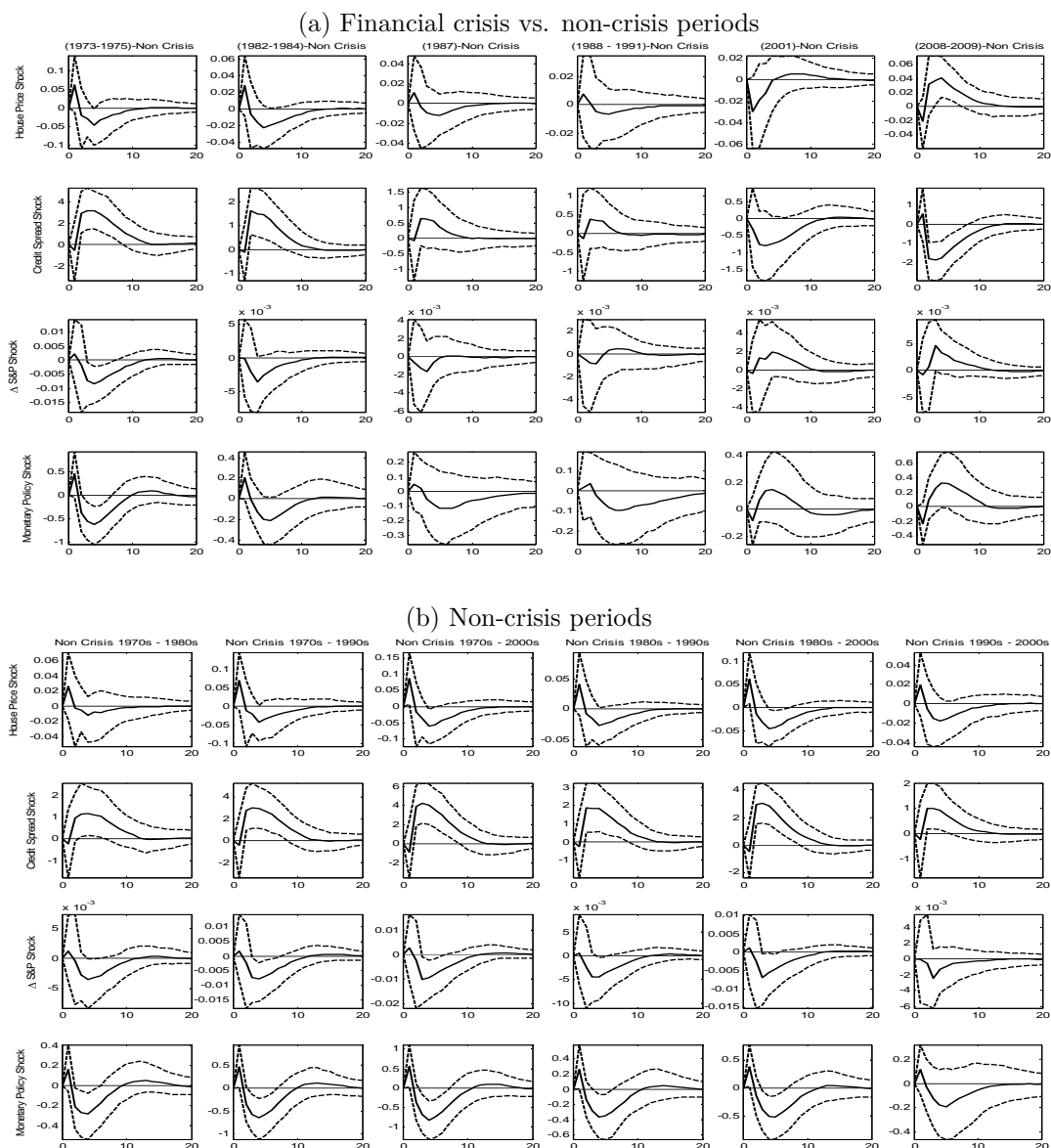
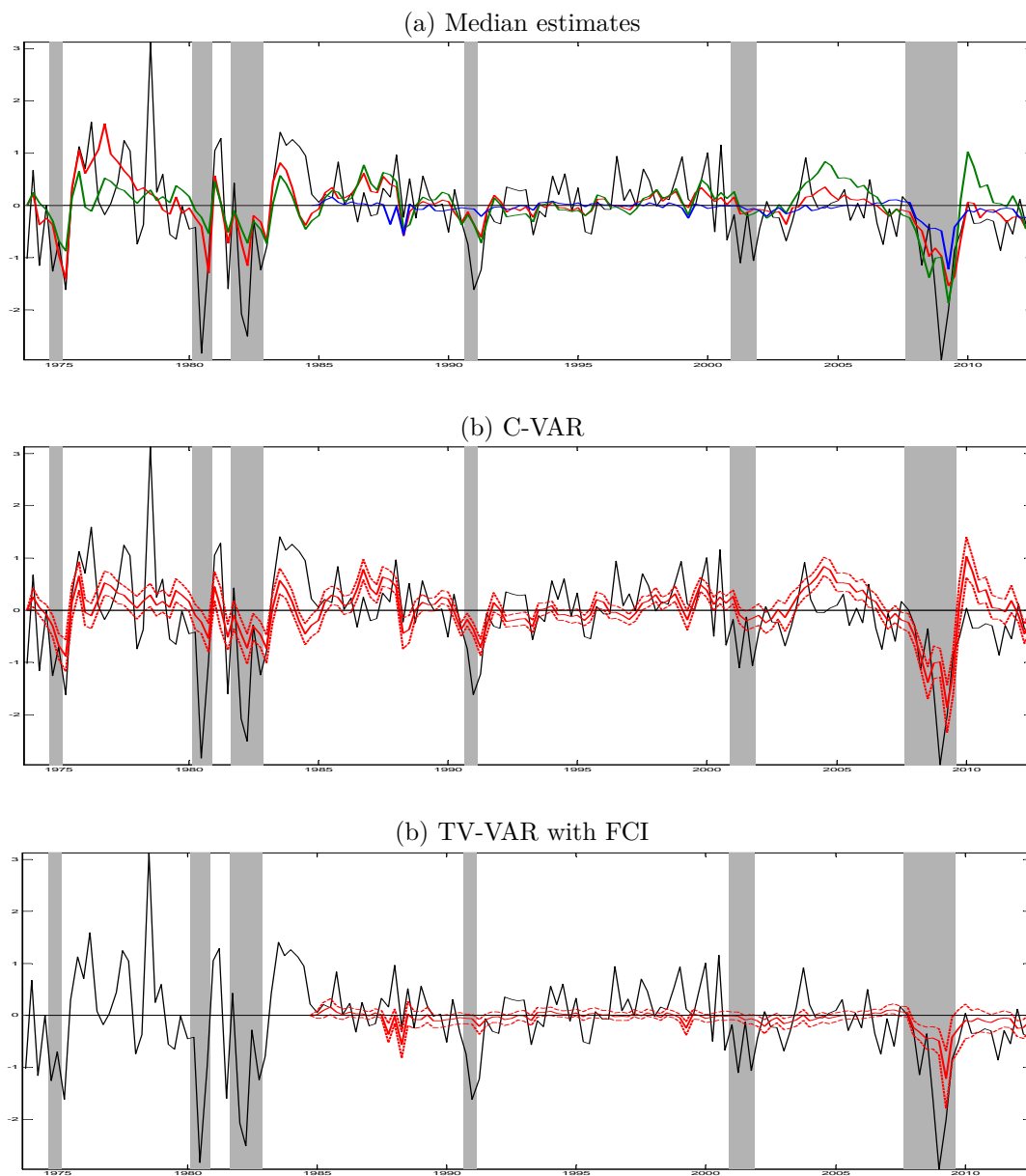


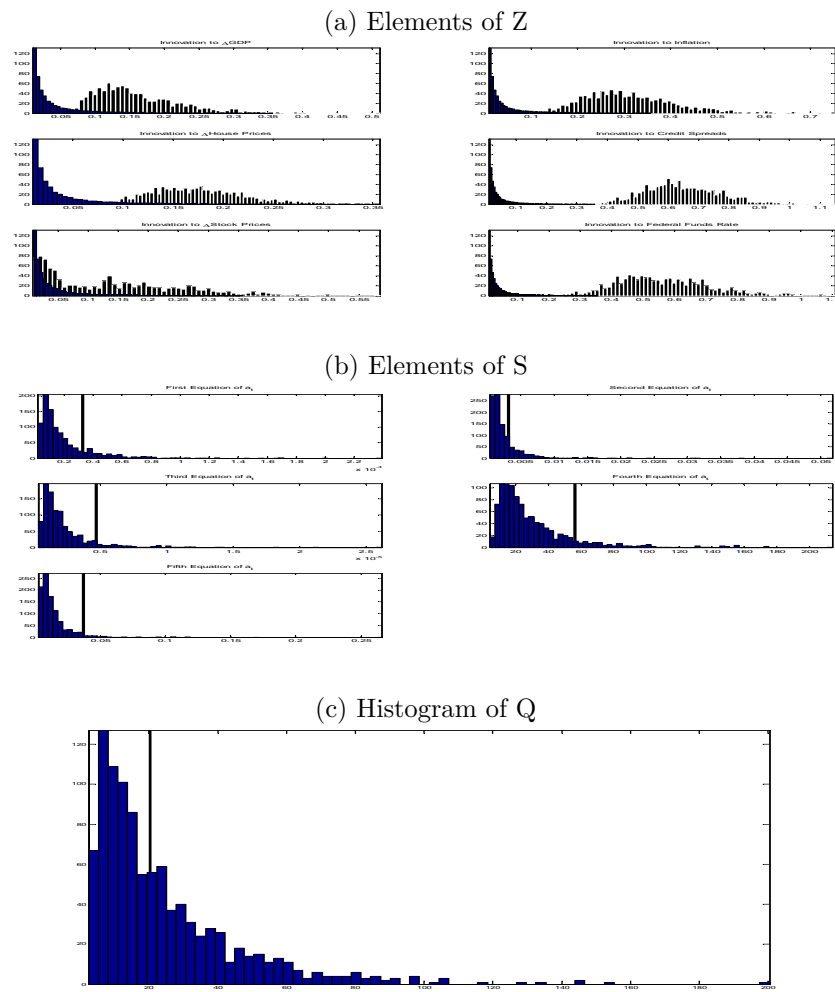
Figure 3.11: Historical Decomposition - TVP-VAR vs. Constant VAR vs. TVP-FCI-VAR



Notes: Black: all shocks, Panel (a): red: derived from TVP-VAR; green: C-VAR; blue: TVP-FCI-VAR (starting in 1984Q3), Panels (b) and (c): solid red: median; dashed red: 16th and 84th percentiles. See also notes to Figure 2 for more information.

3.10 Appendix to Chapter 3

Figure 3.12: Prior (blue) and posterior (black) distributions



Notes: Trace statistics are shown in panels (b) and (c).

Figure 3.13: Results of test for convergence of the hyperparameters and the states

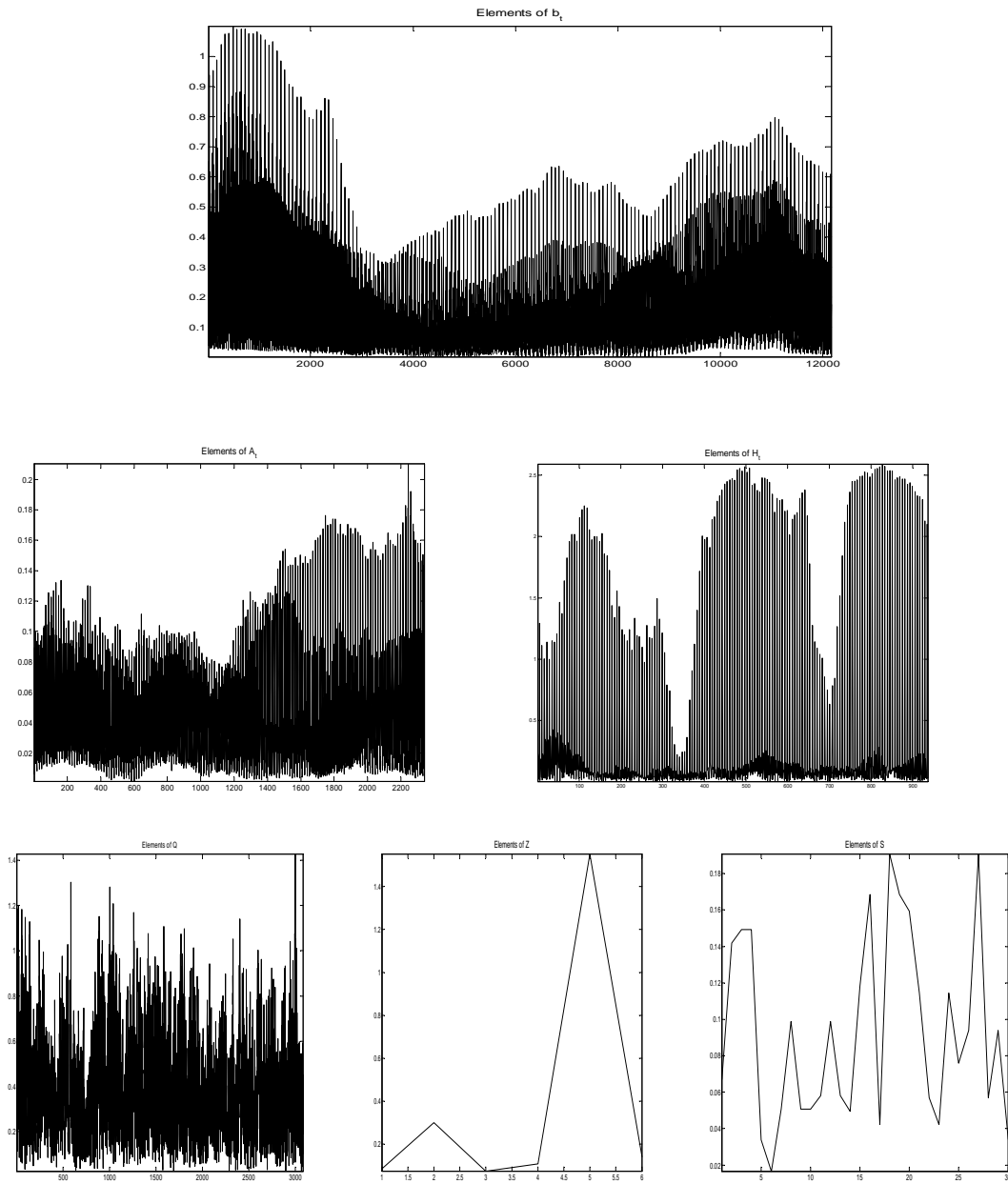
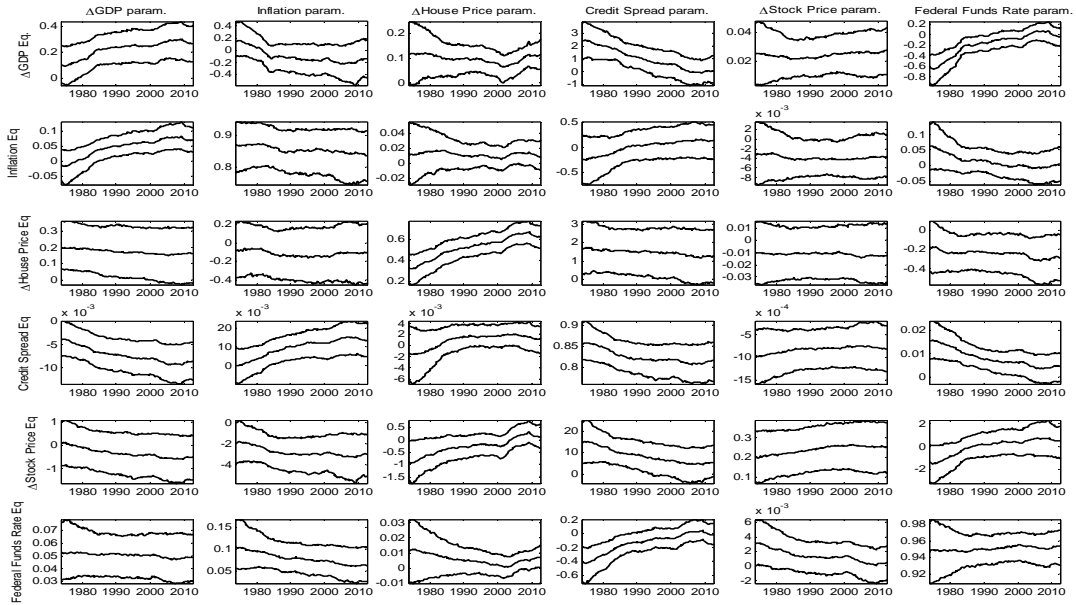


Figure 3.14: Parameter evolution

(a) Autoregressive parameters summed over lags (elements of B_t)



Contemporaneous relations (elements of A_t)

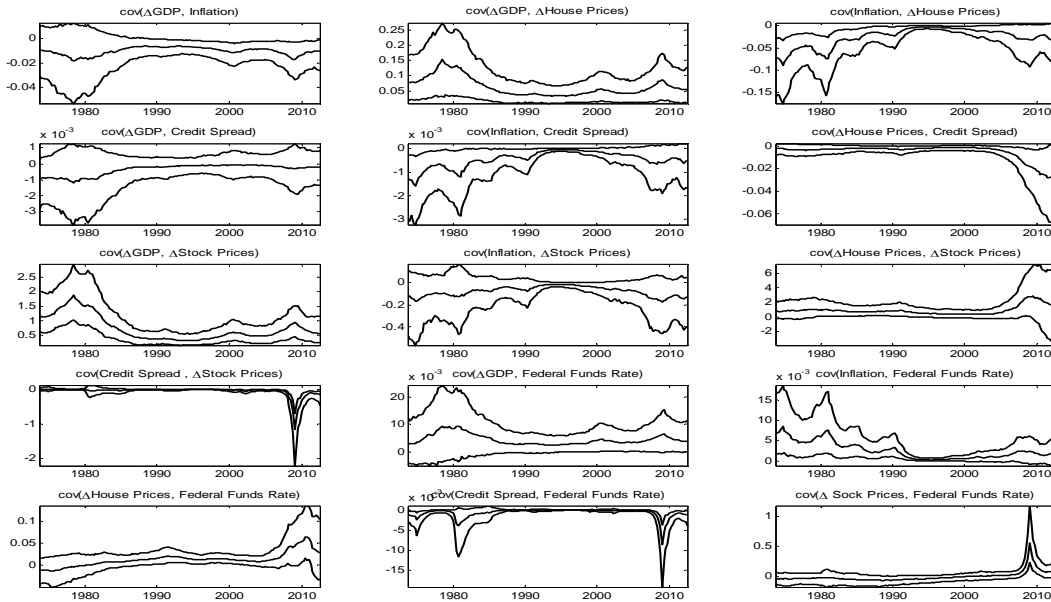


Figure 3.15: Impulse responses of GDP growth to unit financial shocks estimated from the C-VAR (median estimates and 1 standard deviation percentiles) and from the TV-VAR on average over the entire period (median estimates)

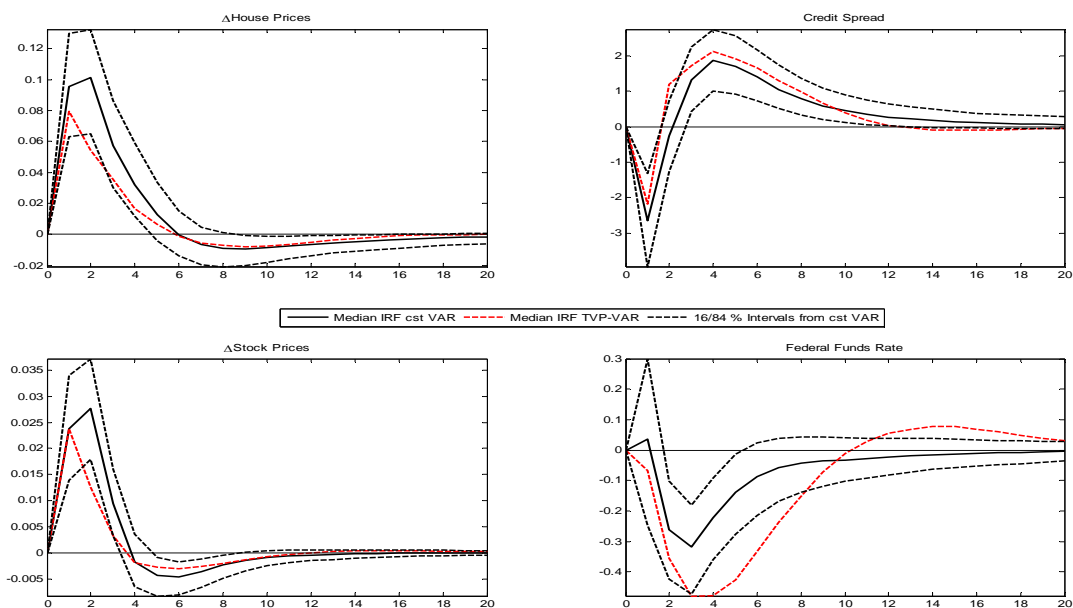
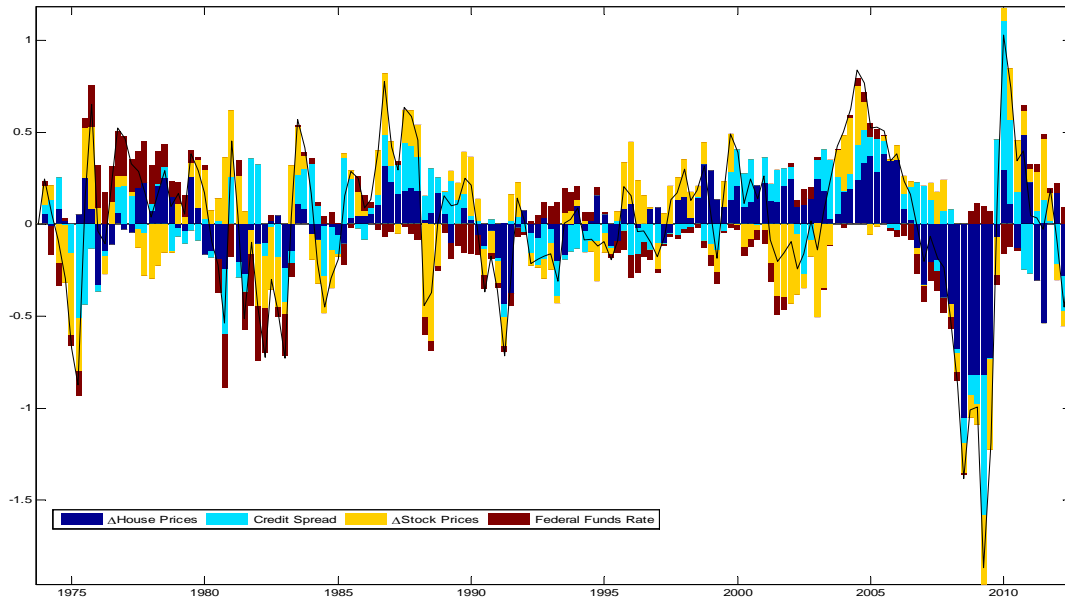
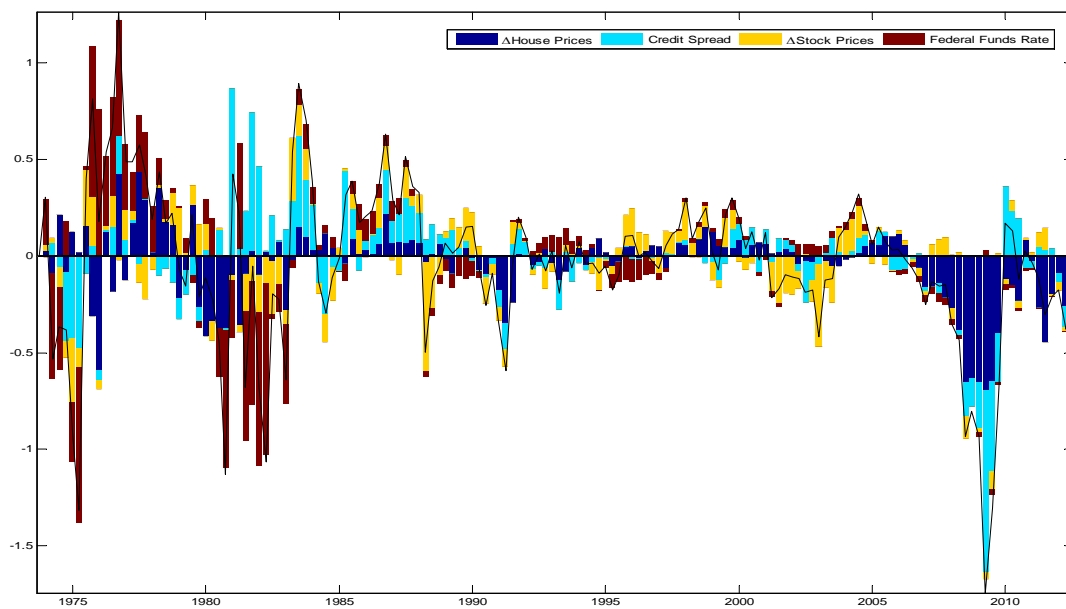


Figure 3.16: Contributions of individual financial shocks from the C-VAR (median estimates)



Notes: see notes to Figure 2.

Figure 3.17: Contributions of individual financial shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation \rightarrow Federal Funds rate \rightarrow credit spread \rightarrow stock price inflation (median estimates)



Notes: see notes to Figure 2.

Figure 3.18: Forecast error variance shares of GDP growth at the 5-year horizon explained by individual financial shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation \rightarrow Federal Funds rate \rightarrow credit spread \rightarrow stock price inflation (median estimates and 1 standard deviation percentiles)

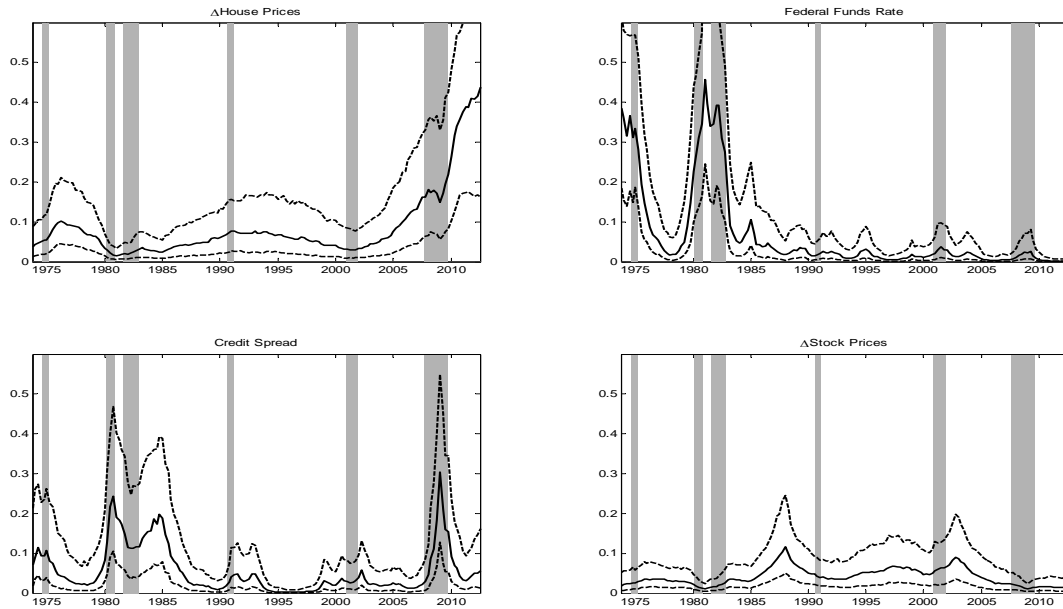


Figure 3.19: Standard deviations of structural shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation \rightarrow Federal Funds rate \rightarrow credit spread \rightarrow stock price inflation (median estimates and 1 standard deviation percentiles)

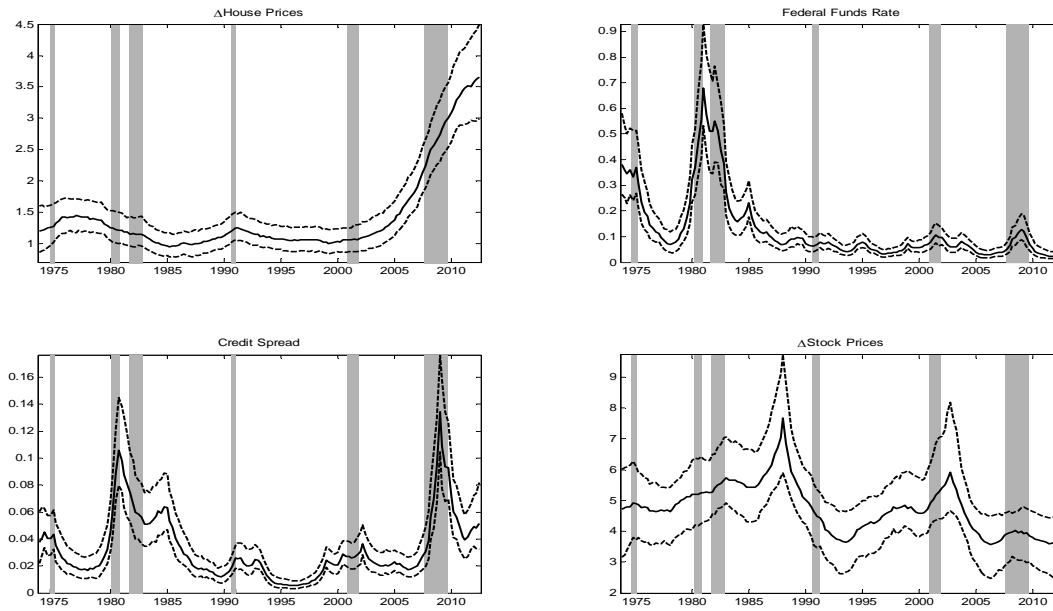


Figure 3.20: Figure A.9: Impulse responses of GDP growth to unit financial shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation \rightarrow Federal Funds rate \rightarrow credit spread \rightarrow stock price inflation (median estimates and 1 standard deviation percentiles)

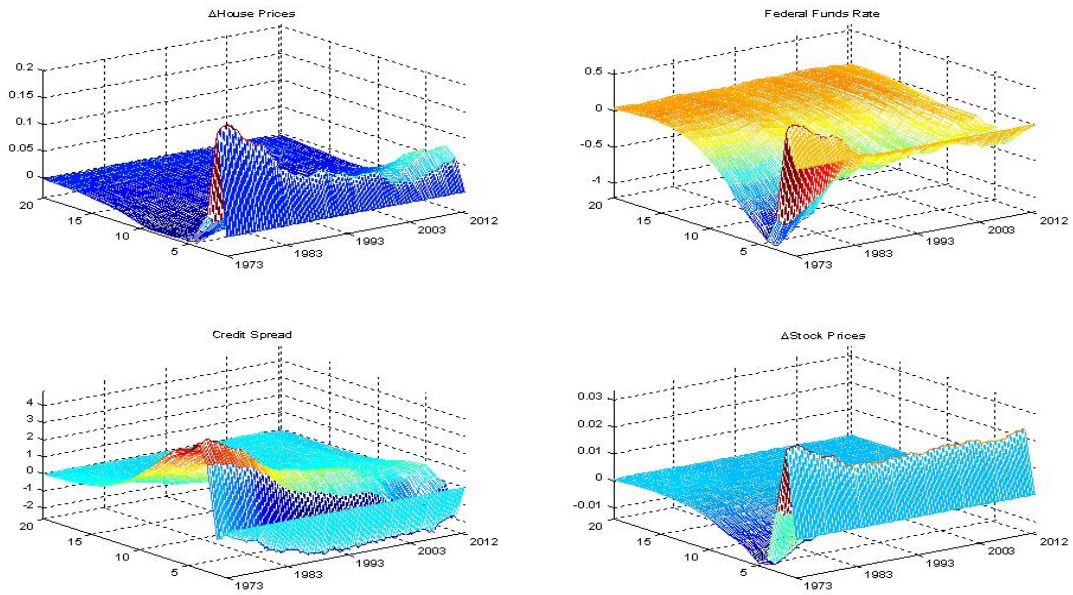
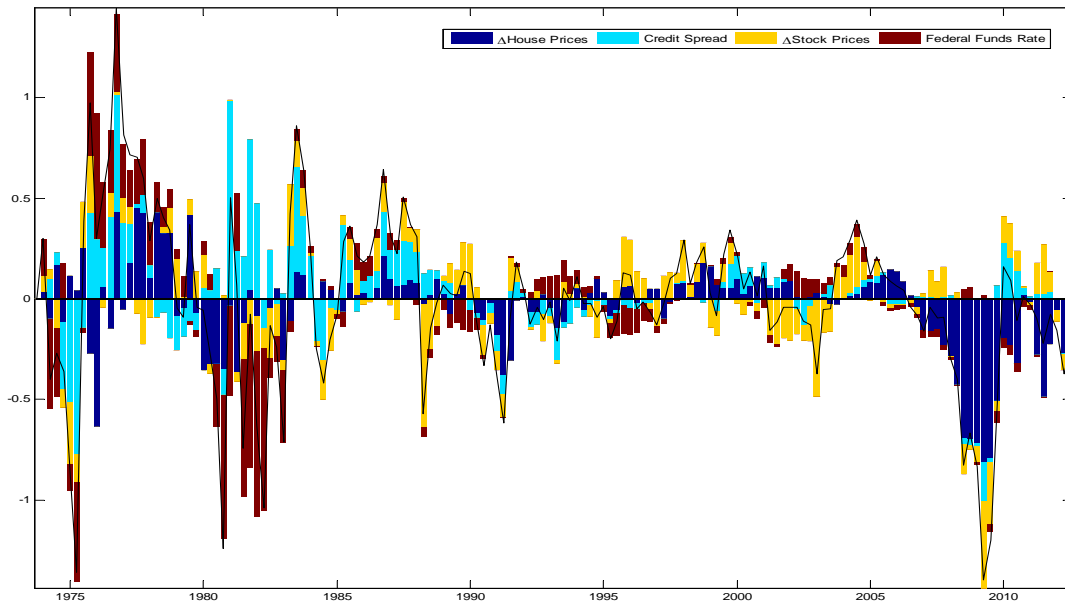


Figure 3.21: Contributions of individual financial shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation \rightarrow stock price inflation \rightarrow credit spread \rightarrow Federal Funds rate(median estimates)



Notes: see notes to Figure 2.

Figure 3.22: Forecast error variance shares of GDP growth at the 5-year horizon explained by individual financial shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation \rightarrow stock price inflation \rightarrow credit spread \rightarrow Federal Funds rate(median estimates)

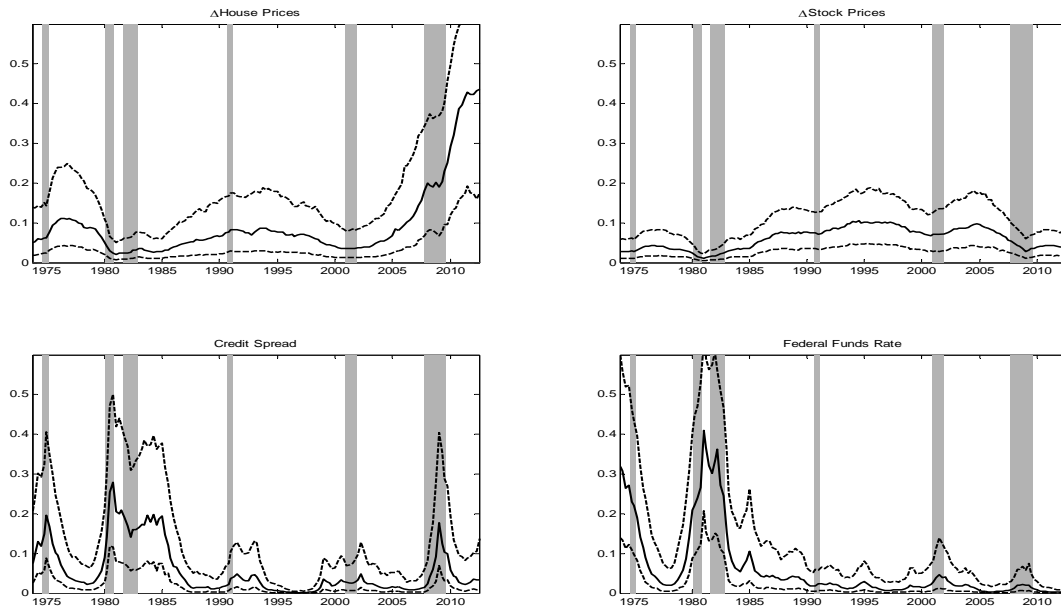


Figure 3.23: Standard deviations of structural shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation \rightarrow stock price inflation \rightarrow credit spread \rightarrow Federal Funds rate (median estimates)

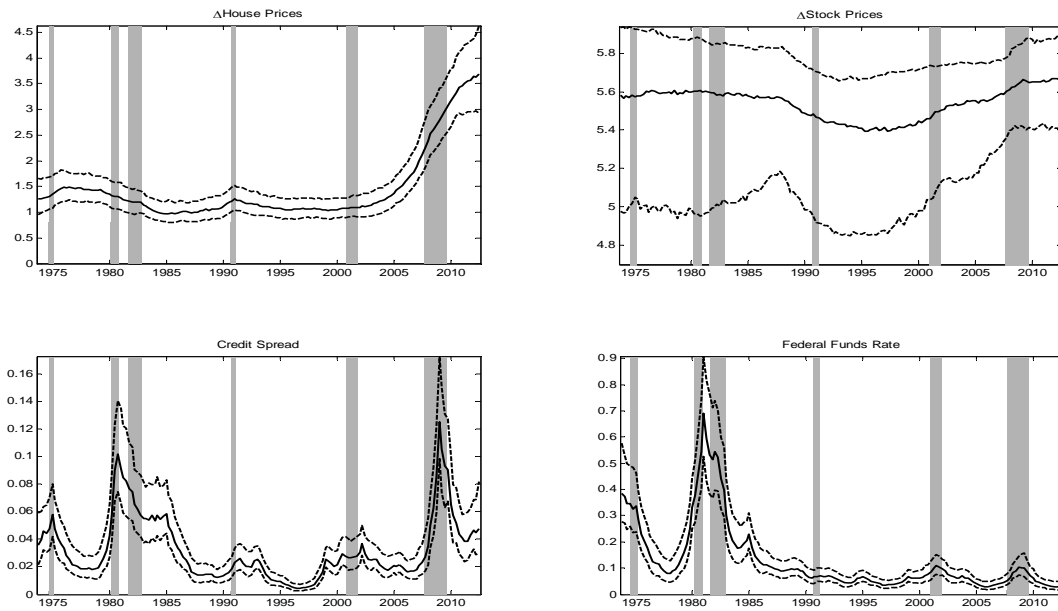
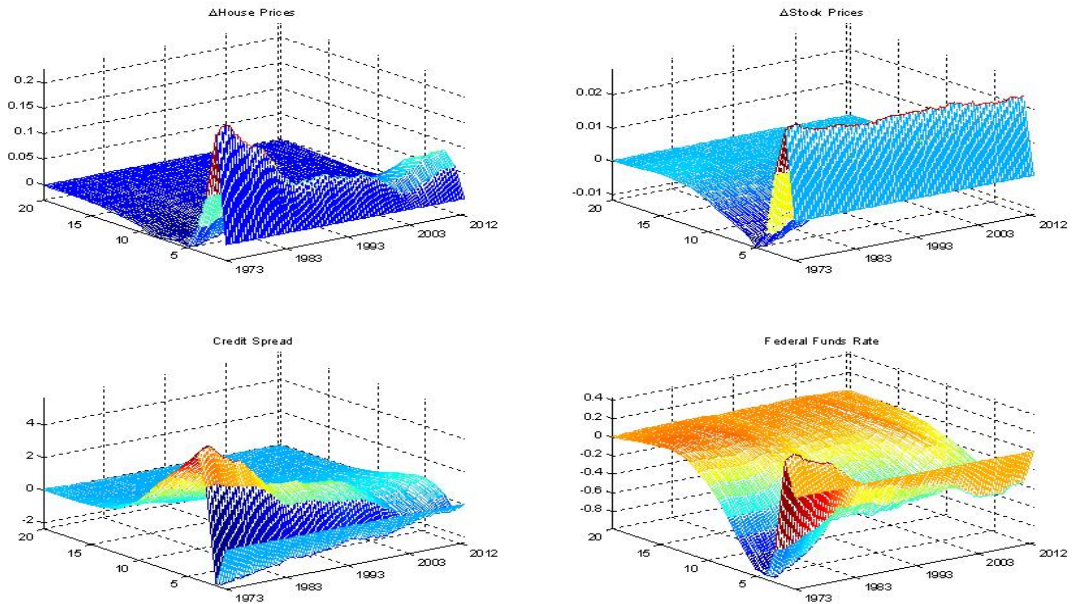


Figure 3.24: Impulse responses of GDP growth to unit financial shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation \rightarrow stock price inflation \rightarrow credit spread \rightarrow Federal Funds rate (median estimates)



Chapter 4

Financial Frictions and Business Cycle Volatility

4.1 Introduction

Financial markets have undergone revolutionary structural changes over the last decades.¹ Although it has long been reckoned that these changes might have altered the dynamics of the economy, little is known about their overall effects on the economy.² An apparently improved efficacy of financial markets, often associated with deregulation and financial innovations, has led many to ascribe part of the reduced macroeconomic volatility in the last decades to a better working financial system (e.g. Boivin and Giannoni 2006). The main punchline is that changes in the structure of financial markets - due to financial innovations and deregulation - allowed consumers and firms to better cushion themselves from macroeconomic shocks; thereby contributing to a more stable economy. The strong belief in the merits of these structural changes has been expressed very clearly by Alan Greenspan: "[...]the growing array of derivatives and the related application of more sophisticated methods for measuring and managing risks had been key factors underlying the remarkable resilience of the banking system, which had recently shrugged off severe shocks to the economy and the financial system."³

¹Sherman (2009) provides a concise outline of the major regulatory changes over the past three decades.

²The first detailed treatment of the interplay between evolutions in financial markets and real activity go back even until Gurley and Shaw (1955)

³Speech given in 2005 at the Federal Reserve Bank of Chicago's Forty-first Annual Conference on Bank Structure

Until recently, most observers would have agreed that financial innovations and deregulation - by reducing financial frictions - contributed to a more stable economy. Indeed, there are empirical and theoretical arguments supporting this view (among others Cecchetti, Flores-Lagunes, and Krause 2006, Dynan, Elmendorf, and Sichel 2006 and Campbell and Hercowitz 2006). This view, however, was shaken by the 2008-2009 Financial Crises. Instead, what seems to be the general theme today is that deregulations and financial innovations increased the vulnerability of the economy to shocks. This changing belief shows how little is known about the effects of the deregulation process, on the one hand, and the emergence of new financial products, on the other hand. The aim of this paper is to enhance our understanding of whether and how these changes affected the behavior of key macroeconomic variables over time, and whether the perceived benefits - or disadvantages - of the financial innovation and deregulation process find support in the data.

The analysis in this paper proceeds in two steps. In the *first step* I estimate a time-varying Bayesian VAR (TVP-VAR) featuring stochastic volatilities along the lines of Cogley and Sargent (2005) and Primiceri (2005). The TVP-VAR includes the standard set of macroeconomic variables: GDP growth, inflation and the Federal Funds rate. I augment the small scale VAR with two financial variables linking the real economy with the banking industry: Growth in total business lending and the loan spread. Based on sign restrictions I identify demand, supply and monetary policy shocks to uncover potential changes in the transmission of these shocks *via* the banking system. The analysis based on the TVP-VAR yields the following main results:

- There has been a strong reduction in the correlations of GDP growth with lending and the loan spread, respectively. The bulk of the reduction in the correlations is concentrated in the early 1980s, thus coinciding with the onset of the 'Great Moderation'.
- The changes in the unconditional correlations can be largely attributed to monetary policy and non-monetary demand shocks. The correlation of GDP growth with lending conditional on the monetary policy shock shows a sign switch from positive values over the 1970s to negative values from the early 1980s onwards. This time variation in the conditional correlation reflects a sizable change in the response of loans to expansionary monetary policy shocks: Over the 'Great Inflation', loans tend to increase in tandem with GDP, but they tend to move in opposite directions over the 'Great Moderation'.

The reduction in the correlation between real activity and the banking variables is in principle consistent with the idea of a reduction in financial frictions: Financial innovations and deregulation, *via* a reduction in financial frictions, dampened business cycle volatility by allowing firms to draw on external financing in economic downturns; consequently there is a reduced comovement between real and financial variables. Using a different methodological approach, Den Haan and Sterk (2011) and Lozej (2010) also document a lower comovement between real and financial variables over the 'Great Moderation' compared to the 'Great Inflation'. The approach taken here, however, allows to uncover a novel result: The largest part of the reduction takes place sharply in the early 1980s, coinciding with the onset of the 'Great Moderation'.

The TVP-VAR, by its very nature, does not allow to uncover the deep structural sources of these changes. Specifically, without a fully structural model, it is not possible to give a definite answer on whether the changes in the correlations and impulse responses are the result of a reduction in financial frictions, or whether other structural changes alone can explain the observed time variation. Therefore, in the *second step* of the analysis, I go one step further by linking the stylized facts from the TVP-VAR to the parameters of a DGSE model featuring a financial accelerator mechanism *à la* Bernanke, Gertler, and Gilchrist (1999). I estimate key parameters of the model by matching the model impulse responses with those obtained from the TVP-VAR using a procedure along the lines of Christiano, Trabandt, and Walentin (2010). The main findings from the estimation of the DSGE model can be summarized as follows:

- Consistent with the 'Bad Luck' hypothesis of the 'Great Inflation', unusually large shocks in the 1970s compared to later periods are crucial to explain the recent macroeconomic performance of the US.
- The 'Great Moderation' is characterized by a more aggressive monetary policy response to inflation compared to the 'Great Inflation'. This finding confirms that the 'Great Inflation' can be explained, at least partly, by 'Bad Policy' (e.g. Judd and Rudebusch 1999, Clarida, Galí, and Gertler 2000 and Cogley and Sargent 2005).
- Most importantly, the key parameter governing the importance of the financial accelerator mechanism, and thus the degree of financial frictions, also exhibits a substantial amount of time variation. The elasticity of the external finance pre-

mium with respect to firm leverage is estimated at 0.16 in 1979s. The corresponding estimate for the year 1997 is significantly smaller and estimated at 0.10.

The results from the estimation of the DSGE model show that the two most prominent explanations for the 'Great Moderation', i.e. a reduction in shock sizes and a change in the conduct of monetary policy, are not sufficient to rationalize the time variation in the impulse responses. Instead, viewed through the lens of a fully structural model, what is necessary to explain the time variation is a reduction in the degree of financial frictions.

The results summarized above provide evidence in support of a reduction in financial frictions over the past decades. The question still open is whether this reduction is due to market driven financial innovations, or due to some regulatory changes. Although the present analysis is not designed to give a final answer to this question, a careful investigation of the timing of the changes in the correlations and impulse responses might at least give an indication. As stated above, the bulk of movement in the correlations and impulse responses is concentrated in the early 1980s. And, as will be explained in more detail below, if the changing financial structure is behind the observed pattern in correlations and impulse responses over time, then the regulatory changes of the early 1980s are likely to be the reason for these changes. By contrast, market driven innovations and the regulatory changes of the 1990s did - if at all - only marginally contribute to the stability of the economy.

The rest of the paper proceeds as follows. Section 4.2 describes the TVP-VAR and the approach to the identification of shocks. In Section 4.3 I present the evidence on time variation from the TVP-VAR. Section 4.4 discusses the estimation of the DSGE model and presents the estimation results obtained for selected periods of the sample. In Section 4.5 I discuss and interpret the results in light of outside evidence. Section 4.6 concludes.

4.2 Methodology

4.2.1 A Time-varying Parameter VAR

The analysis departs from a m -dimensional vector Y_t , which includes output growth, inflation, growth in commercial and industrial loans, the loan spread (defined as the bank prime lending rate less the Federal Funds rate) and the Federal Funds rate. All variables have been transformed to non-annualized quarter-on-quarter growth rates by

taking log-first differences of the level variables, except of the loan spread and the Federal Funds rate which enter in levels. The sample period extends from 1951Q3 to 2008Q2.⁴ I assume that Y_t follows a time varying parameter VAR(p) model:

$$Y_t = B_t' X_t + u_t, \quad E(u_t) = 0, \quad E(u_t u_t') = \Sigma_t, \quad (4.2.1)$$

with B_t' a $(m \times 1 + mp)$ coefficient matrix and X_t a $(1 + mp \times 1)$ vector containing a constant and two lags of Y_t . I further define $b_t = \text{vec}(B_t)$, and assume that b_t evolves according to a driftless random walk:

$$b_t = b_{t-1} + \eta_t, \quad \eta_t \sim N(0, Q),$$

Q being a positive definite matrix. Following standard practice, as e.g. in Cogley and Sargent (2005), I impose a stability constraint on the time-varying parameters to enforce stationarity of the system. That is, I include an indicator function that rejects those draws for which the roots of the associated VAR polynomial lie inside the unit circle.

Moreover, we have:

$$\Sigma_t = A_t^{-1} H_t A_t^{-1'}. \quad (4.2.2)$$

The matrix A_t is lower triangular, with ones on the main diagonal and containing in the below diagonal elements the contemporaneous relations $a_{ij,t}$ between the variables in the model. The matrix H_t is a diagonal matrix containing the reduced form stochastic volatilities $h_{i,t}$ of the innovations to the VAR.

Both the contemporaneous relations $a_{ij,t}$ and the innovations' volatilities $h_{i,t}$ are allowed to drift over time. Following Primiceri (2005) we collect the diagonal elements of H_t in the vector $h_t = [h_{1,t}, h_{2,t}, h_{3,t}, h_{4,t}, h_{5,t}, h_{6,t}]'$, and assume that

$$\ln h_t = \ln h_{t-1} + v_t, \quad v_t \sim N(0, Z),$$

Z being a diagonal matrix. Similarly,

$$a_t = a_{t-1} + \tau_t, \quad \tau_t \sim N(0, S),$$

⁴Unconventional monetary policy and a binding zero lower bound after mid-2008 impedes the use standard identification restrictions on monetary policy shocks. I therefore do not extend the sample to the most recent periods.

with a_t being constructed by row-wise stacking of the non-zero and non-one elements of the matrix A_t , namely, $a_t = [a_{21,t}, a_{31,t}, a_{32,t}, \dots, a_{54,t}]'$, and S being a positive definite, block diagonal matrix.

I estimate the model using a Markov-Chain-Monte-Carlo (MCMC) algorithm as explained in Cogley and Sargent (2005), Primiceri (2005) or Benati (2008). The MCMC algorithm simulates the joints posterior distribution by sequentially drawing from the conditional distributions, which all have familiar form (see e.g. Cogley and Sargent 2005, Primiceri 2005 or Benati 2008). After a sufficiently long period of "burn-in draws", which I set to 75,000, the sequence of draws from the conditional densities converges in distribution to the desired joint distribution. In order to reduce the autocorrelation in the simulated draws I draw 25,000 values from the target distribution keeping only every 10th draw to ascertain randomness.

4.2.2 Identification of Structural Shocks

I identify aggregate supply, aggregate demand and monetary policy shocks using sign restrictions in the spirit of Faust (1998), Canova and de Nicolo (2003) and Uhlig (2005). I implement the sign restrictions following the procedure suggested by Rubio-Ramírez, Waggoner, and Zha (2010) (see also Benati and Mumtaz 2007). Specifically, let $\Sigma_t = P_t D_t P_t'$ be the eigenvalue-eigenvector decomposition of the time-varying reduced form variance-covariance matrix of the VAR. Further, let $\hat{A}_{0t} \equiv P_t D_t^{1/2}$, and Ω be a 5×5 random matrix drawn from an independent standard normal distribution. The QR decomposition of Ω delivers $\Omega = QR$. The time-varying impact matrix of the structural shocks is then computed as $\bar{A}_{t0} = \hat{A}_{0t} Q'$. If the impulse responses generated by the impact matrix \bar{A}_{t0} satisfy the sign restrictions, I keep the matrix, otherwise I discard it. I keep drawing from the random matrix Ω until I obtain an impact matrix which satisfies all sign restrictions simultaneously. This procedure is repeated for each draw from the posterior distribution and for each point in time t .

I use standard identification restrictions which can be derived from the most commonly used DSGE models, and also from the structural DSGE model laid out in Section 4.4. Specifically, contractionary monetary policy shocks increase the Federal Funds rate and reduce prices and output. The loan spread increases in tandem with the monetary policy rate. Aggregate demand shocks are the only shocks which move output, prices, the loan spread and the Federal Funds rate in the same direction. Finally, aggregate supply shocks move prices and output in opposite directions, and the Federal Funds rate

in the same direction as prices. All sign restrictions are imposed on impact and the first four quarters after the shock. The identifying restrictions are summarized in Table 4.1.

A few explanatory notes concerning the restrictions on the banking variables are in order: The positive reaction of the loan spread after aggregate demand and monetary policy shocks is derived from the financial accelerator model used in Section 4.4. In this DSGE model with financial frictions, the external finance premium - the theoretical counterpart to the empirical loan spread - increases after contractionary monetary policy shocks and expansionary non-monetary demand shocks (e.g. government spending shocks). Next, note that I do not restrict the loan volume to follow any pre-specified scheme. There are two reasons for this choice: First, in order to test the hypothesis of a reduction in financial frictions, I want to be as least restrictive on the loan volume as possible. Leaving the loan response unrestricted, I let the data speak freely concerning any changes in the dynamic interrelation between loans and other macroeconomic variables. Second, given that the restrictions I impose are sufficient to disentangle the macroeconomic shocks, restrictions on the response of loans are simply not needed.

Finally, the VAR contains five variables, hence there are two additional shocks which drive the dynamics of the system. I do not try to identify all structural shocks. The sign restrictions imposed are sufficient to uniquely identify supply, demand and monetary policy shocks. The two unidentified shocks will pick up all other shocks hitting the economy (e.g. house price or financial shocks), to the extent that these shocks are not already captured by the identified shocks. As such, leaving two of the shocks unrestricted acts as a buffer mechanism and minimizes concerns due to potential omitted variables biases (see Canova, Gambetti, and Pappa 2007 for a similar discussion).⁵

⁵In order to make sure that the unrestricted shocks do not lead to the same behavior of the variables as the three identified shocks, I impose the additional requirement that the remaining two shocks do not have the same properties as the three identified shocks. Strictly speaking, the unrestricted shocks are therefore not unrestricted but restricted not to be aggregate supply, aggregate demand or monetary policy shocks.

4.3 Evidence from the TVP-VAR

4.3.1 Unconditional Moments

I start by presenting some unconditional second moments in Figure 4.1.⁶ Panel (a) and (b) of Figure 4.1 present the medians of the posterior distribution of the unconditional GDP growth-lending correlation and GDP growth-loan spread correlation. Alongside the correlations I also plot the unconditional volatility of GDP growth. The time-varying variance-covariance matrix of the variables in the VAR, from which I derive the volatility and correlations, is computed using a second-moment counterpart of the Beveridge-Nelson trend as shown in Cogley, Primiceri, and Sargent (2010).⁷ I focus on the volatility and correlations of GDP growth because this variable is generally used as reference indicator for studying structural changes in the economy (see e.g. Gali and Gambetti 2009).

Concerning the volatility of GDP, its evolution over time is similar to the one presented elsewhere (e.g. Gali and Gambetti 2009 or Cogley, Primiceri, and Sargent 2010). The volatility is highly elevated in the 1970s, i.e. during the time of the 'Great Inflation'. Starting in the early 1980s - coinciding with the beginning of the Volcker disinflation period - the GDP growth volatility falls dramatically. After a short time period, the volatility is more than 3 times smaller compared to its peak values at the beginning of the 1980s.

Moving to the time-varying unconditional correlations, panel (a) presents the correlation between GDP growth and lending. The figure depicts a pronounced downward trend in the correlation. Between 1967 and 1980, the correlation of GDP growth with lending averaged slightly below 0.3. There are two spikes in the correlation occurring around 1975 and 1980, coinciding with the two large recessions during the 'Great Inflation'. From the year 1980 onwards this correlation then sharply drops within a couple of quarters to values below 0.15, remaining at these lower values from then on. A similar picture can be observed for the correlation of GDP growth with the loan spread in panel (b), although the changes are less pronounced. Over the 'Great Inflation', the GDP

⁶All results are based on a sample of 500 draws, randomly selected from the 2500 draws generated by the MCMC algorithm described above.

⁷For this, let $z_{t+1} = \mu_t + \Phi_t z_t + \varepsilon_{z,t}$ be the companion form of the VAR, then the variance-covariance matrix of z_{t+1} is given by $\text{var}(z_{t+1}) = \sum_{h=0}^{\infty} (\Phi_t^h) \text{var}(\varepsilon_{z,t}) (\Phi_t^h)'$. The infinite sum represents the solution to a discrete-time Lyapunov equation which can be solved using the Matlab function `DLYAP.M` or a 'doubling algorithm' as explained e.g. in Anderson and Moore (1979)[pp. 158-160] or Anderson, McGrattan, Hansen, and Sargent (1996).

growth-loan spread correlation takes large negative values around -0.45 but experiences a strong reduction (in absolute terms) to values around -0.23 in the early 1980s. Mirror imaging the GDP growth-lending correlation, there are pronounced spikes around the years 1975 and 1980. The GDP growth-loan spread correlation shows a pronounced drop occurring in the second half of the 1990s. The reduction in the correlation initiated in the second half of the 1990s continues until the end of the sample. At the end of the sample period the unconditional correlation between GDP growth and the loan spread is around -0.5 and thus close to the large negative values of the 1970s.

The results for the unconditional correlations provide first evidence for fundamental changes in the relation between the real economy and the banking system. The reduction in the correlation between GDP growth and lending is consistent with the finding reported in Den Haan and Sterk (2011) and provides a first indication in favor of a reduction in financial frictions. The approach taken here, however, allows to uncover a novel result: The largest part of the reduction takes place sharply in the early 1980s, coinciding with the pronounced drop in the volatility of GDP growth. However, the analysis so far does not allow to distinguish whether this pattern is the result of a structural change in the economy or whether some shocks, inducing a specific correlation, have merely become more or less important over time. I therefore now turn to the inspection of the conditional correlations and the impulse response analysis.

4.3.2 Structural Evidence

Conditional Correlations

Figure 4.2 presents the correlations between the main variables conditional on the three identified shocks. The correlation of GDP growth with lending and the loan spread, conditional on supply (red dotted line), demand (blue dashed lines) and monetary policy shocks (black solid line), are shown in panel (a) and (b) of Figure 4.2, respectively.

Starting with the conditional correlation between GDP growth and lending in panel (a) of Figure 4.2 it is readily apparent that supply and demand shocks are not the main drivers of the observed changes in the unconditional correlation uncovered in the previous section. Both conditional correlations fluctuate around their average values without any tendency to increase or decrease substantially. By contrast, the correlation conditional on the monetary policy shock exhibits a pattern which fits well the time variation in the unconditional correlation. With a few exceptions the correlation conditional on the

monetary policy shock takes on positive values over the entire 1970s. In the early 1980s the correlation experiences a substantial drop from its positive peak in 1981 of nearly 0.60 to around -0.40 in 1986. From then on, this conditional correlation remains negative, hovering around values of -0.35. Hence, the observed drop in the unconditional GDP growth-lending correlation can be attributed entirely to a changing comovement induced by monetary policy shocks.

The conditional correlation of GDP growth with the loan spread shown in panel (b) of Figure 4.2 tell a similar story. The correlation conditional on supply shocks exhibits large fluctuations around its average value of roughly 0. Consequently, this conditional correlation often switches signs from positive to negative values and back, without clear pattern over time which could explain the time variation in the corresponding unconditional correlation. The correlations conditional on the demand and monetary policy shocks show a similar evolution over time: a marked increase in the early 1980s, a period of a rather low comovement between 1984 and around 1998, followed by a pronounced drop at the end of the sample period. For the correlation conditional on the demand shock the reduction observed at the end of the sample is so pronounced that the correlation exceeds (in absolute terms) the one observed in the 1970s.

The analysis of the conditional correlations has shown some substantial time variation in the comovement between the real economy and the banking variables. Furthermore, the time variation in the conditional correlations indicates that 'Bad Luck' alone, reflecting exceptionally large shocks, cannot be the only underlying reason for the elevated macroeconomic volatility of the 1970s. Instead, the results point towards the existence of some 'true' structural changes in the economy. Obviously, the time variation in the conditional correlations must be driven by similar changes in the dynamic comovement between the variables. In the next section I will therefor briefly discuss the impulse responses to the identified shocks.

Impulse Response Analysis

The analysis of the conditional correlations has revealed that much of the changes in the comovement between the real economy and the banking sector can be attributed to monetary policy and demand shocks. In the following I will therefore only present the impulse responses of the variables to these two shocks.

Figure 4.3 and Figure 4.5 show the medians of the posterior distribution of the impulse responses of all variables to a one standard deviation monetary policy and demand

shock, respectively. Figure 4.4 and Figure 4.6 present the median impulse responses together with the one standard deviation probability bands at each point in time for three selected horizons. The impulse responses of GDP growth, inflation and lending have been accumulated and are shown in levels.⁸

As expected, the impulse responses to monetary policy shocks reveal a considerable amount of time variation (Figure 4.3). We observe a positive reaction of GDP, which is large and displays substantial persistence in the 1970s. The magnitude of the effect, however, decreases dramatically with the beginning of the 1980s and remains subdued from then on. A similar pattern over time is also visible in the response of loans. However, different from the GDP response, the loan response switches signs at medium and longer horizons. This pattern is even more visible in Figure 4.4. The plot shows that on impact the loan response is negative throughout the entire sample period. During the 1970s the medium and long run responses of loans turn positive while they remain negative for the period after the early 1980s. The sign switch in the impulse responses at medium/longer horizons materializes within a few quarters and coincides with the more muted response of output to the monetary policy shock. Hence, the observed sign switch in the correlation conditional on monetary policy shocks between GDP growth and lending uncovered above is the result of a substantial change in the behavior of loans in response to monetary policy shocks.

Figure 4.5 and Figure 4.6 show that over the 1970s, a one standard deviation demand shock triggers a pronounced increase in the short and medium run in GDP and Prices. Mirror imaging the effects after monetary policy shocks, in the early 1980s this pattern changes to a much more muted price and output response. The most striking changes are however observable in the response of lending. During the entire 1970s, loans do hardly change at all in the short and medium run. Based on the median estimate the response of loans to a demand shock in the 1970s is, if anything, to slightly decrease in the medium run. Comparable to the behavior of loans following a monetary policy shock, at the beginning of the 1980s this pattern changes. Based on the median estimate, the response of loans switches signs and becomes positive in the medium term, with the positive effect gradually increasing until the most recent period.

Finally, note that the substantially larger impact effects of monetary policy and demand shocks on GDP and Prices during the 1970s indicate that at least part of the

⁸Note that the impulse response functions are subject to a good amount of econometric uncertainty. Unfortunately, this is a common feature of the very highly parameterized TVP-VARs. For the remainder of the discussion I will therefore concentrate on the median estimates of the impulse responses.

'Great Inflation' can be attributed to larger shocks. Hence, the results from the impulse response analysis are consistent with the 'Bad Luck' hypothesis of the 'Great Inflation', and are in line with a series of work using a similar methodological framework, e.g. Benati and Mumtaz (2007) and Canova, Gambetti, and Pappa (2007). However, changing shock sizes alone cannot explain the time variation in the conditional correlations and the changing comovement of the impulse responses of the variables. Instead, these results point toward 'true' structural changes in the economy, which will be examined more formally in the next section.

4.4 Evidence from a DSGE Model with Financial Frictions

The preceding analysis has revealed a number of results supporting the view that structural changes in the banking industry affected the dynamics of the US economy. However, only a fully structural model allows to reveal whether the observed changes in the impulse responses are consistent with a reduction in financial frictions over the last decades. Therefore, in order to move beyond the stylized facts produced by the TVP-VAR, I use a standard DSGE model featuring financial frictions to investigate whether the time variation in the VAR impulse responses can be mapped into changes in some structural parameters of the model. In doing so, I estimate a number of key parameters of the model for specific periods by matching the impulse responses from the TVP-VAR with the impulse responses from the DSGE model. To estimate the model, I use a variant of the Bayesian impulse response matching approach introduced by Christiano, Trabandt, and Walentin (2010).

The Model

I use a version of the canonical New Keynesian DSGE model as presented in Smets and Wouters (2003), Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007). To introduce a non-trivial role for financial market friction, I extended the model with the financial accelerator mechanism along the lines of Bernanke, Gertler, and Gilchrist (1999). Since the model is well known, I present only the log-linearized version of the model that is estimated. The presentation of the model closely follows De Graeve (2008).

From the household sector optimization conditions it is possible to derive the following equation describing the evolution of aggregate consumption C_t :

$$C_t = \frac{h}{1+h}C_{t-1} + \frac{1}{1+h}E_t C_{t+1} + \frac{\sigma_c - 1}{(1+\lambda_w)(1+h)}\sigma_c(L_t - E_t L_{t+1}) - \frac{1-h}{1+h\sigma_c}(r_t - E_t \pi_{t+1}).$$

This consumption equation stems from a utility function non-separable in consumption C_t and labor L_t , featuring external habit persistence h . The parameter σ_c captures the intertemporal elasticity of substitution of consumption, $r_t - E_t \pi_{t+1}$ is the ex-post real interest rate, and λ_w represents the equilibrium wage markup which derives from the households monopoly power over the supply of its labor.

Household labor supply is differentiated and households act as price setters in the labor market. I assume that the wage setting process is subject to Calvo-style wage setting rigidities. Specifically, in each period t the probability that the household can change its nominal wage is constant and given by $1 - \xi_w$. The remaining wages which are not adjusted are partially indexed to past inflation. The degree of partial wage indexation is governed by the parameter γ_w . When $\gamma_w = 0$ there is no indexation and wages which are not adjusted remain constant; with $\gamma_w = 1$ indexation to past inflation is perfect. These assumptions give rise to the following equation describing the dynamics of nominal wages w_t :

$$w_t = \frac{\beta}{1+\beta}E_t w_{t+1} + \frac{1}{1+\beta}w_{t-1} + \frac{\beta}{1+\beta}E_t \pi_{t+1} - \frac{1+\beta\gamma_w}{1+\beta}\pi_t + \frac{\gamma_w}{1+\beta}\pi_{t-1} - \frac{(1-\beta\xi_w)(1-\xi_w)}{1+\beta(1+(1+\lambda_w)\sigma_l/\lambda_w)\xi_w}(w_t - \sigma_l L_t - \frac{\sigma_c}{1-h}(C_t - hC_{t-1}))$$

with β denoting the household's discount factor and σ_l the inverse of the household's elasticity of labor supply to the wage rate.

The final consumption good is produced in a perfectly competitive market by combining the output of intermediate good firms. A Cobb-Douglas production function augmented with variable capital utilization costs relates total supply to labor L_t and capital services K_t :

$$Y_t = \alpha K_{t-1} + \frac{\alpha}{\psi} r_t^k + (1-\alpha)L_t$$

with α denoting the capital share in the production process, ψ is the elasticity of the capital utilization cost function to capital, and r_t^k represents the real rental rate of capital.

Aggregated labor demand is given by the following standard labor demand function, which is decreasing in wages and increasing in the rental rate of capital:

$$L_t = -w_t + \left(1 + \frac{1}{\psi}\right) r_t^k + K_{t-1}.$$

Each intermediate good producer has monopoly power in the goods market and acts as a price setter. Similar to the labor market, firms are subject to Calvo-style rigidities in adjusting their prices. In each period, the probability that the firm can change its price is constant and given by $1 - \xi_p$. The remaining prices are partially indexed to past inflation. The degree of partial price indexation is governed by the parameter γ_p . This setup generates the following New Keynesian Phillips curve extended to include price indexation:

$$\pi_t = \frac{\beta}{1 + \beta\gamma_p} E_t \pi_{t+1} + \frac{\gamma_p}{1 + \beta\gamma_p} \pi_{t-1} + \frac{1}{1 + \beta\gamma_p} \frac{(1 - \beta\xi_p)(1 - \xi_p)}{\xi_p} (\alpha r_t^k + (1 - \alpha)w_t)$$

Capital producers work in a perfectly competitive market. Increasing the supply of capital by changing the flow of investment (I_t) is costly.

The evolution of the capital stock is standard and given by:

$$K_t = (1 - \tau)K_{t-1} + \tau I_{t-1},$$

with τ denoting the depreciation rate of capital.

The investment trajectory derived from the capital producer's optimization condition implies that the current period investment decision depends on past and future investment, and on the value of already installed capital q_t

$$I_t = \frac{1}{1 + \beta} I_{t-1} + \frac{\beta}{1 + \beta} E_t I_{t+1} + \frac{1}{\phi(1 + \beta)} q_t$$

where ϕ is the parameter governing the cost of adjusting investments.

Entrepreneurs buy the entire capital stock from the capital producers at a given price q_t and use this capital in production at time $t + 1$. The corresponding q -equation is given by

$$E_t R_{t+1}^k = \frac{(1 - \tau)}{\bar{R}^k} E_t q_{t+1} + \frac{(\bar{R}^k - 1 + \tau)}{\bar{R}^k} E_t r_{t+1}^k - q_t;$$

where \bar{R}^k denotes the steady state return to capital.

In order to buy the capital stock k_t valued at q_t , entrepreneurs can draw on internal net worth n_t . However, I assume that entrepreneurs net worth is not sufficient to buy the entire capital stock. Consequently, entrepreneurs must turn to banks to finance the residual part of $Q_t K_t - N_t$ with bank loans L_t . Hence, in each period entrepreneurs borrow one period loans l_t according to:

$$\left(\frac{K}{N} - 1\right) l_t = \frac{K}{N}(q_t + k_t) - n_t,$$

where $\frac{K}{N}$ denotes the steady state capital-to-net worth ratio.

So far, the model presented is basically identical to a standard DSGE model without financial friction. However, following Bernanke, Gertler, and Gilchrist (1999), the presence of financial frictions - reflecting a costly-state verification problem between firms and banks - imply that entrepreneurs face an external finance premium s_t that drives a wedge between the expected return on capital and the risk free rate:

$$s_t \equiv E_t R_{t+1}^k - (r_t - E_t \pi_{t+1}) = -\epsilon E_t (n_{t+1} - q_t - k_{t+1}).$$

The key parameter governing the importance of the costly-state verification problem is given by ϵ which measures the elasticity of the external finance premium with respect to firm leverage.

Entrepreneurial net worth n_t accumulates according to

$$n_{t+1} = \gamma \bar{R}^k \left(\frac{K}{N} (R_t^k - E_{t-1} R_t^k) + E_{t-1} R_t^k + n_t \right)$$

where γ denotes the entrepreneurial survival rate.

The standard goods market equilibrium stipulates that

$$Y_t = c_y C_t + \tau k_y I_t + \epsilon_t^g$$

where c_y and k_y denote the steady state ratio of consumption and capital to output, and ϵ_t^g is an exogenous AR(1) shock process $\epsilon_t^g = \rho_g \epsilon_{t-1}^g + u_t^g$ representing a demand shock (potentially initiated by a government spending shock).

The model is closed by a standard Taylor-rule monetary policy reaction function:

$$r_t = \rho r_{t-1} + (1 - \rho)(r_\pi \pi_t + r_y Y_t) + r_{\Delta Y}(Y_t - Y_{t-1}) - \epsilon_r.$$

The parameter ρ represents the smoothing parameter, r_π and r_y are the reaction parameters to inflation and the output gap, respectively. The parameter $r_{\Delta Y}$ can be interpreted as a speed limit. Finally, ϵ_r represents an exogenous i.i.d policy shock.

Impulse Response Matching

In order to investigate the quantitative implications of the DSGE model values must be assigned to the structural parameters of the model. The parameters of the models are split into two groups. The first group consists of parameters which I assume to be constant over time and which are calibrated at fixed values. The second group consists of parameters which are allowed to change over time. To obtain values for the time-varying parameters the model impulse responses are matched with the VAR impulse responses at different times. I focus on two different periods, the fourth quarters of 1979 and 1997, representing respectively the 'Great Inflation' and the 'Great Moderation'. The procedure used to match the DSGE and VAR impulse responses is a close variant of the limited information Bayesian impulse response matching approach of Christiano, Trabandt, and Walentin (2010).

Specifically, denote the vectors containing the VAR impulse responses to the monetary policy and demand shock with $\hat{\phi}_{mp}$ and $\hat{\phi}_d$. Each vector contains the dynamic responses of the five variables for a horizon of 28 quarters. The dimension of each vector is thus (140×1) . Denote the vector stacking both impulse response vectors as $\hat{\phi} = (\hat{\phi}'_{mp} \hat{\phi}'_d)'$ which has dimension (280×1) . Given that the number of observations T in $\hat{\phi}$ is large, classical asymptotic sampling theory states that:

$$\sqrt{T}(\hat{\phi} - \phi(\theta_0)) \stackrel{a}{\sim} N(0, W(\theta_0, \zeta)),$$

where θ_0 represents the true values of the parameters that are estimated, $\phi(\theta_0)$ the respective model impulse responses and ζ contains the true values of the shock parameters that are in the model which are however not formally included in the empirical analy-

sis (see Christiano, Trabandt, and Walentin 2010). The asymptotic distribution of the vector $\hat{\phi}$ can be expressed in the following way:

$$\hat{\phi} \stackrel{a}{\sim} N\left(\phi(\theta_0), \frac{W(\theta_0, \zeta)}{T}\right).$$

The next step of the analysis consists in choosing a value of θ that produces model impulse responses as close as possible to the VAR impulse responses. For this, I treat $\hat{\phi}$ as data and define the approximate likelihood of the data as a function of the model parameters θ :

$$f(\hat{\phi}|\theta) = \left(\frac{1}{2\pi}\right)^{\frac{T}{2}} \left|\frac{W(\theta_0, \zeta)}{T}\right|^{-\frac{1}{2}} \times \exp\left[-\frac{1}{2}(\hat{\phi} - \phi(\theta))' \left(\frac{W(\theta_0, \zeta)}{T}\right)^{-1} (\hat{\phi} - \phi(\theta))\right].$$

The value of $W(\theta_0, \zeta)/T$ in the likelihood function is treated as fixed. Following Hofmann, Peersman, and Straub (2012) I assume $W(\theta_0, \zeta)/T$ to be diagonal. The elements on the diagonal consist of the variances of the posterior distribution of the impulse responses for each horizon. Specified in this way, the weighting matrix $W(\theta_0, \zeta)/T$ attaches less weight to those impulse responses which are estimated less precisely.

Treating the function $f(\hat{\phi}|\theta)$ as the likelihood of the empirical impulse responses $\hat{\phi}$ and applying Bayes Theorem, it follows that the Bayesian posterior of the parameters of the model θ conditional on the empirical impulse responses $\hat{\phi}$ is given by

$$f(\theta|\hat{\phi}) = \frac{f(\hat{\phi}|\theta)p(\theta)}{f(\hat{\phi})}.$$

The marginal data density is given by $f(\hat{\phi})$ and the priors on θ are denoted by $p(\theta)$. The mode of the posterior distribution of θ can be computed by simply maximizing the value of the numerator of the posterior of θ , since the denominator is not a function of θ .

The main difference between the approach take here and the method described in Christiano, Trabandt, and Walentin (2010) is that the Bayesian TVP-VAR does not produce a point estimate which could be used as single data vector $\hat{\phi}$. Instead, the TVP-VAR produces 500 different impulse responses which all satisfy the sign restrictions. As an alternative, I follow Hofmann, Peersman, and Straub (2012) who propose to compute the posterior mode for each of the 500 impulse responses and to report the resulting posterior distribution of the modes.

Results

Table 4.2 reports the values of the parameters which are treated as fixed. The parameters are taken from the existing literature and are pretty standard. See, for instance, Smets and Wouters (2007), De Graeve (2008) and Brzoza-Brzezina and Kolasa (forth.). I also experimented with allowing for time variation in some of the calibrated parameters. Although some parameters exhibit significant time variation (especially the price and wage indexation parameters), the main results presented in this section were not affected. In order to keep the number of results small and the section focused on the main point, I present only the results from the exercise with time variation in the monetary policy rule, the shock processes and the financial frictions parameter.

Table 4.3 presents the priors of the parameters which are used to match the empirical impulse responses. I report the prior density with the corresponding mean and standard deviation, and the admissible parameter range. The priors are specified in a way which is consistent with the previous literature (see De Graeve 2008, Gilchrist, Ortiz, and Zakrajsek 2009 and Hofmann, Peersman, and Straub 2012). I allow for time variation in the shock processes, i.e. in the standard deviation of the monetary policy and the demand shock, and the autoregressive parameter of the demand shock. This takes into account that time variation in the shock sizes is a crucial feature of the last decades. Furthermore, in order to account for the changing conduct of monetary policy (see e.g. Clarida, Galí, and Gertler 2000), I allow for time variation in the monetary policy rule. Following Christiano, Trabandt, and Walentin (2010) and Hofmann, Peersman, and Straub (2012), I restrict the inflation reaction parameter to be strictly greater than one. This rules out the possibility of indeterminate solutions of the model. Finally, to account for the hypothesis that structural changes in the banking industry reduced financial frictions, I allow the elasticity of the external finance premium to firm leverage (ϵ) to be time-varying. The higher the parameter ϵ , the more reactive the external finance premium to variations in the balance sheet of borrowers. Observing a reduction in this parameter over time can therefore be interpreted as a reduction in financial frictions.

In Figure 7 I present the distribution of the model implied impulse responses for the two periods. Alongside the model impulse responses, I also plot the corresponding VAR impulse responses. Comparing the model and the VAR impulse responses shows that the DSGE model is quite successful in reproducing the evidence from the VAR. There are only two exceptions. First, the loan response in 1979 shows that the DSGE model is not flexible enough to reproduce the positive reaction of loans to the monetary

policy shock at shorter horizons. However, after around 8 to 10 quarters the model implied loan response turns positive and the probability bands overlap with those from the VAR. Second, the model impulse response of the loan spread in 1997 is more muted following the demand shock. In all other cases, the probability bands of the model impulse responses overlap with those from the TVP-VAR, nearly at all horizons. This is reassuring and suggests that the DSGE model is a reasonable approximation to the data.

In the last two columns of Table 4.3 I summarize the results from the impulse response matching procedure concerning the estimated parameters. Comparing the distributions of the stochastic shock processes, a clear story emerges. Both, monetary policy and demand shocks are estimated to be significantly larger over the 'Great Inflation' compared to the 'Great Moderation'. Based on the median estimate, the size of the monetary policy shock (demand shock) drops from a value of 0.45 (1.00) in 1979 to only 0.045 (0.21) in 1997. Hence, the results from the impulse response matching exercise document clearly what is now common wisdom: While the 'Great Moderation' can be characterized as a period in which the economy was hit by relatively small shocks, the 'Great Inflation' is, at least partly, triggered by unusually large shocks. The results for the shock processes therefor support a large literature suggesting that 'Bad Luck', in the sense of a series of relatively large shocks hitting the economy, contributed to the very volatile behavior of the US economy in the 1970s (see e.g. Benati and Mumtaz 2007, Justiniano and Primiceri 2008 and Canova and Gambetti 2009).

Concerning the monetary policy rule, we observe that there is significant movement in the reaction parameters to inflation and the output gap. First, the reaction to the output gap is significantly larger in the 1970s compared to later periods. A tentative explanation for this results is that the VAR impulse responses capture the systematic overestimation of the output gap in the 1970s (see Orphanides 2001). The model seems to interpret this as stronger reaction to the output gap. Second, in 1979 the inflation reaction parameter is estimated to be around 1.12, which is significantly smaller than the corresponding value of 1.48 in 1997. The pattern of time variation in the inflation reaction parameter supports the second main hypothesis towards explaining the 'Great Inflation', i.e. 'Bad Policy'. According to e.g. Judd and Rudebusch (1999) and Clarida, Galí, and Gertler (2000), erratic monetary policy, by reacting too little to inflation, contributed to the very volatile nature of the economy in the 1970s.

Most importantly for the present analysis, the parameter representing the degree of financial friction - the elasticity of the external finance premium to firm leverage - also changes significantly over time. In 1979 the median value of the parameter is given by 0.16, compared to a significantly smaller value of 0.10 in 1997. These values are both within the parameter range reported in De Graeve (2008); the value in 1979 however at the very upper end. The value of 0.10 in 1997 is close to the median value reported in De Graeve (2008) and somewhat larger than the estimates in Christensen and Dib (2008) and Meier and Müller (2006). Note that in both periods the amount of information in the likelihood function about this parameter is substantial: In 1997, the size of the posterior one standard deviation probability band is only around half the size of the corresponding prior probability band; in 1979 it is even only one-fifth.⁹

The results from the model estimation show that the time variation in the VAR impulse responses are mapped into a more muted structural response of the banking system to changes in the balance sheet of borrowers in the DSGE model. This indicates that the time variation uncovered by the TVP-VAR is indeed consistent with a reduction in financial frictions over the last decades. Furthermore, the evidence presented in this section also shows that the most prominent explanations for the recent US macroeconomic history alone are not sufficient to explain the time variation in the impulse responses: Although the model ascribes part of the movement in the impulse responses to changes in shock sizes and changes in the conduct of monetary policy, it also pushes for a reduction in financial frictions in order to explain the changing behavior of the macroeconomy over time.

4.5 A Narrative Account of the Observed Changes

The estimation of the DSGE model suggests that the reduction in financial frictions, potentially caused by structural changes in the financial industry, is an important element in the list of structural changes experienced by the U.S. economy. The question remaining is whether the observed changes can be linked to historical events related to financial markets. The two most important changes which come to mind are regulatory changes and the process of market induced financial innovation over the last decades.

⁹The prior one standard deviation bounds implied by a beta distribution with mean 0.05 and standard deviation 0.025 are given by [0.026; 0.074].

In Figure 8 I plot the effective Federal Funds rate together with the interest rate ceilings imposed by Regulation Q on the four most important deposit accounts. The plot makes clear that the 1970s is a period during which banks were heavily constrained in their interest rate decisions. Most strikingly, the periods in which the Federal Funds rate strongly exceeds the ceilings on deposit rates (1974/1975 and in the late 1970s/early 1980s) coincide well with the stylized facts uncovered by the VAR analysis: Around 1974/75 as well as in the late 1970s/early 1980s the correlation of lending and the loan spread with economic activity soured to their record heights. These periods also exhibit the strongest transmission of demand and monetary policy shocks to lending, and, although to a lower extent, to prices and output. Although for some deposit accounts (large time deposits) interest rate ceilings were removed already in 1973, small saving and deposit accounts remained constrained and it is possible that these constraints were partly responsible for the increasing comovement of the banking variables with economic activity.¹⁰

If binding interest rate constraints contributed to the strong comovement and shock transmission, why do we observe the changes in these statistics in the early 1980s although Regulation Q was active until 1986? An possible explanation is the Garn-St Germain Depository Institutions Act (GSGDIA) of 1982. Faced with large outflows of savings balances from banks to money market funds, the GSGDIA authorized banks to offer two ceiling free accounts: the Money Market Deposit Account (MMDA) and the Super NOW account. These two accounts proved to be very popular, attracting more than \$400 billion to banks within the first year (see Morris and Walter 1998). The flexibility brought by this regulatory changes has very likely alleviated some problems caused by the binding interest rate ceiling on savings and deposits account.

The second landmark decision in the deregulation process is the Depository Institutions Deregulation and Monetary Control Act (DIDMCA) of 1980. Besides increasing deposit insurance from \$40,000 to \$100,000 and providing for the gradual phase-out of Regulation Q, the DIDMCA implemented a uniform reserve requirement for all depository institutions to ensure the Federal Reserve's ability to conduct monetary policy. The uniform reserve requirement was a reaction to a wave of withdrawals of member banks from the Federal Reserve System (for a discussion see FDIC 1997 and the literature therein).

¹⁰In fact, the impact of the binding constraints was felt most by smaller banks that depended more heavily on small retail deposits as opposed to larger banks which were able to partly offset the Regulation Q constraints *via* large-denomination CDs (DeYoung 2007).

The above discussion suggests that the stylized facts revealed above can be linked relatively well to the financial deregulation process of the early 1980s. By contrast, relating the sharp and permanent changes in the shock transmission and correlations to the introduction of new financial products is more difficult. The effects of new financial products are likely felt only gradually with the dissemination of the innovation in the economy. This is visualized in Figure 9, plotting the percentage of loans securitized relative to total loans outstanding for different loan categories.¹¹ The figure shows that securitization of business loans started to grow rapidly only from the mid 1990s onwards. In 1989 only a mere 0.1% of all outstanding commercial and industrial loans were securitized. Hence, securitization in the business loan segment alone can hardly be one of the underlying forces responsible for the structural changes at the beginning of the 1980s. Still, securitization of other loan categories had potentially positive spillovers to business lending. One candidate for this explanation is securitization of single-family home mortgages. Indeed, the share of securitized home mortgages started to grow fast from around 1981 onwards. However, the observed changes in the correlations and in the shock propagation *via* the banking sector have been very quick and sharp. The increasing use of mortgage securitization, by contrast, appears to be a much more gradual phenomenon. Hence, for this hypothesis to be more convincing, the transition to a "high securitizing financial system" should have been more instantaneous.

4.6 Conclusion

The emergence of new and more sophisticated financial product and the deregulation of the financial industry over the past decades has often been associated with a more robust financial system. Furthermore, many argued that these financial innovations had beneficial effects for the real economy by reducing the extent of financial frictions in the economy. The 2008-2009 financial crisis has fundamentally changed the perception about these developments. In this paper, I have explored to what extent aggregate data informs us about the contribution of changes in the financial system to the stability of the economy.

¹¹Securitization is of course not the only financial market innovation appearing over the last decades. Still, without doubt it is the most important and most often discussed product. Furthermore, the general consensus seems to be that among all new financial products loan securitization is by far the most influential for macroeconomic dynamics.

The analysis presented herein provides three new results. First, a time-varying Bayesian VAR featuring stochastic volatility shows that the interaction between the real economy and the banking system has undergone substantial changes over the last decades. Most importantly, the bulk of the changes materializes sharply in the early 1980s, thus coinciding with the onset of the 'Great Moderation'. Second, the estimation of a DSGE model featuring financial frictions shows that the time variation in the dynamic interrelation between the banking industry and the real economy is indeed compatible with a reduction in financial frictions: The key parameter governing the importance of financial frictions turns out to be substantially larger in the 1970s compared to the 1990s. Third, a careful examination of the exact timing of the changes indicates the following: If the changing financial structure is supposed to be the driving force behind the time variation in relation between the real economy and the financial sector, then the regulatory changes of the early 1980s are more likely to be the roots of these changes than the market driven financial innovations of the last decades.

4.7 References

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4.8 Tables

Table 4.1: Sign Restrictions

	Output	Prices	Loans	loan spread	FFR
Monetary Policy	↑	↑		↓	↓
Demand	↑	↑		↑	↑
Supply	↑	↓			↓

Table 4.2: Calibrated Parameters

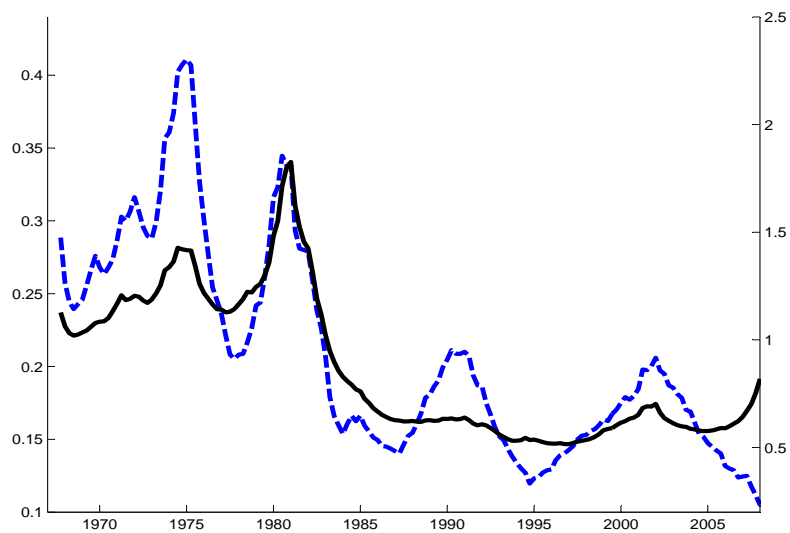
h	habit formation	0.50
β	discount factor	0.99
σ_c	inverse of ela. of substitution	2
σ_l	inverse of ela. of labor supply w.r.t. real wage	2
λ_w	wage markup	0.6
γ_w	partial indexation of wages	0.4
γ_p	partial indexation of prices	0.4
ξ_p	Calvo prices	0.75
ξ_w	Calvo wages	0.75
α	capital share in production	0.3
τ	capital depreciation rate	0.025
ψ	ela. of capital util. cost	0.3
ϕ	investment adjustment cost parameter	2.5
γ	entrepreneurial survival rate	0.977
$\frac{K}{N}$	steady state ratio of capital to net worth	2

Table 4.3: Priors and Posterior Estimates

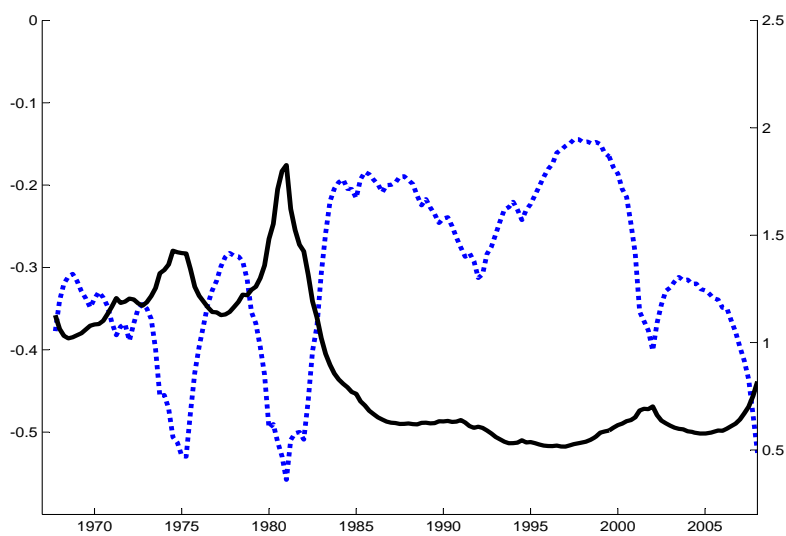
Parameters		Prior		Posterior	
		Density [Bounds]	Mean (Std. dev)	1979 Median [16%,84%]	1997 Median [16%,84%]
ϵ	Ela. of EFP to Leverage	Beta [0,0.5]	0.05 (0.025)	0.167 [0.163,0.173]	0.102 [0.091,0.118]
ρ	Taylor smoothing	Beta [0,1]	0.8 (0.10)	0.881 [0.866,0.914]	0.894 [0.884,0.927]
r_π	Taylor inflation	Gamma [1.01,4]	1.50 (0.20)	1.128 [1.075,1.185]	1.480 [1.336,1.526]
r_y	Taylor output	Gamma [0,2]	0.10 (0.075)	0.334 [0.282,0.343]	0.119 [0.028,0.247]
$r_{\Delta Y}$	Taylor Δ output	Gamma [0,1]	0.075 (0.05)	0.225 [0.088,0.390]	0.109 [0.023,0.251]
ρ_g	Autocorr. demand shock	Beta [0,1]	0.80 (0.10)	0.806 [0.794,0.831]	0.78 [0.718,0.844]
σ_g	Std. dev demand shock	Uniform [0,10]	0.00 (10)	1.001 [0.675,1.231]	0.215 [0.125,0.241]
σ_r	Std. dev mon. policy shock	Uniform [0,10]	0.00 (10)	0.454 [0.388,0.588]	0.045 [0.035,0.052]

4.9 Figures

Figure 4.1: Unconditional Moments



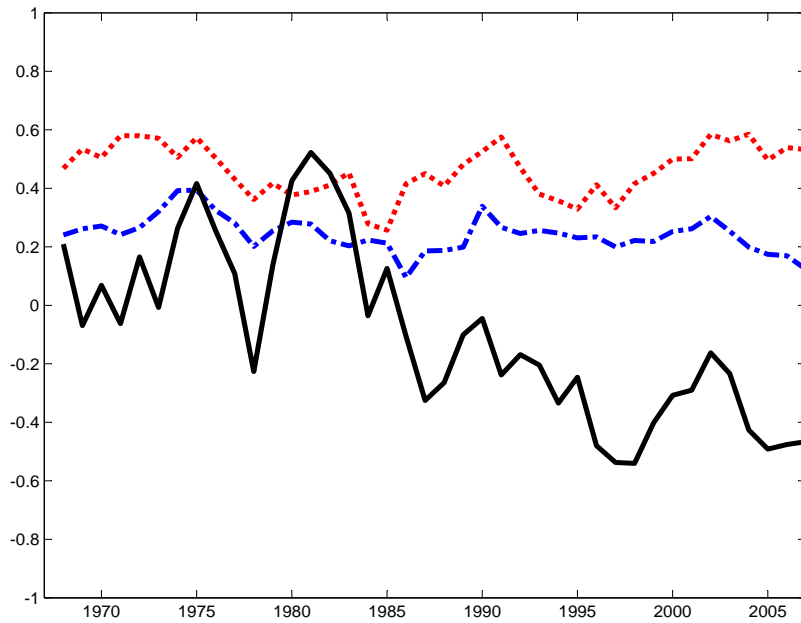
(a) $\rho(\Delta Y; \Delta L)$: blue; $\sigma(\Delta Y)$: black



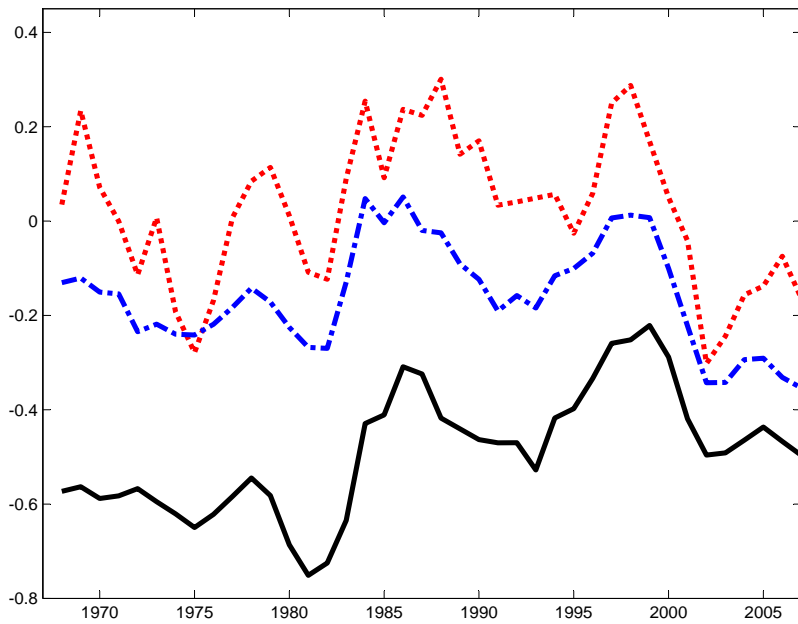
(b) $\rho(\Delta Y; LS)$: blue; $\sigma(\Delta Y)$: black

Notes: This figure shows the unconditional time-varying standard deviation of GDP growth (black solid line) together with the unconditional time-varying correlation between GDP growth and lending (Panel (a)), and the unconditional time-varying correlation between GDP growth and the loan spread (Panel (b))

Figure 4.2: Conditional Correlations



(a) $\rho(\Delta Y; \Delta L)$



(b) $\rho(\Delta Y; LS)$

Notes: This figure shows the time-varying correlation between GDP growth and lending (Panel (a)) and the time-varying correlation between GDP growth and the loan spread (Panel (b)) conditional on monetary policy shocks (black), demand shocks (blue) and supply shocks (red)

Figure 4.3: Impulse Response Functions to Monetary Policy Shocks

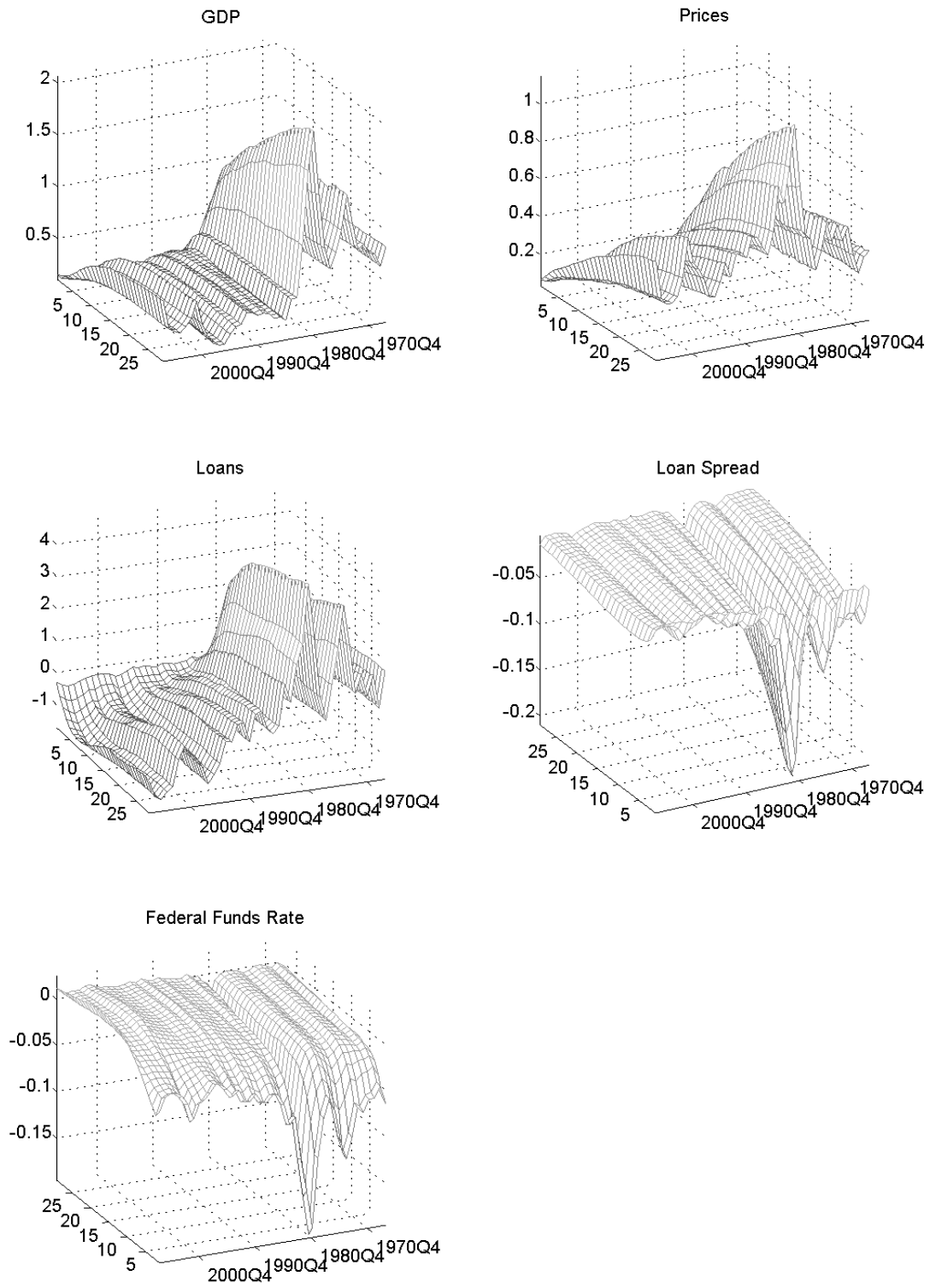


Figure 4.4: Impulse Response Functions to Monetary Policy Shocks - Selected Horizons

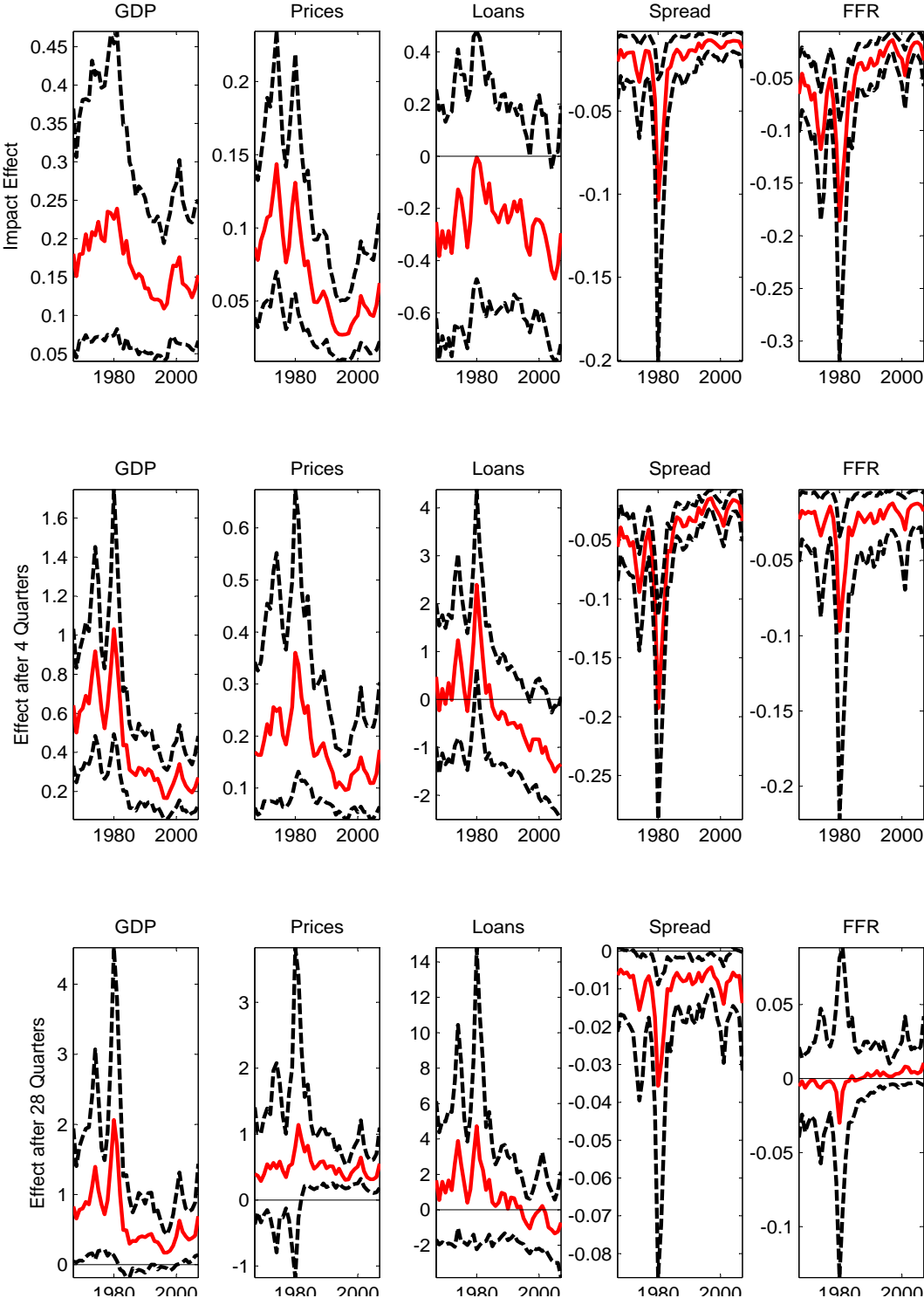


Figure 4.5: Impulse Response Functions to Demand Shocks

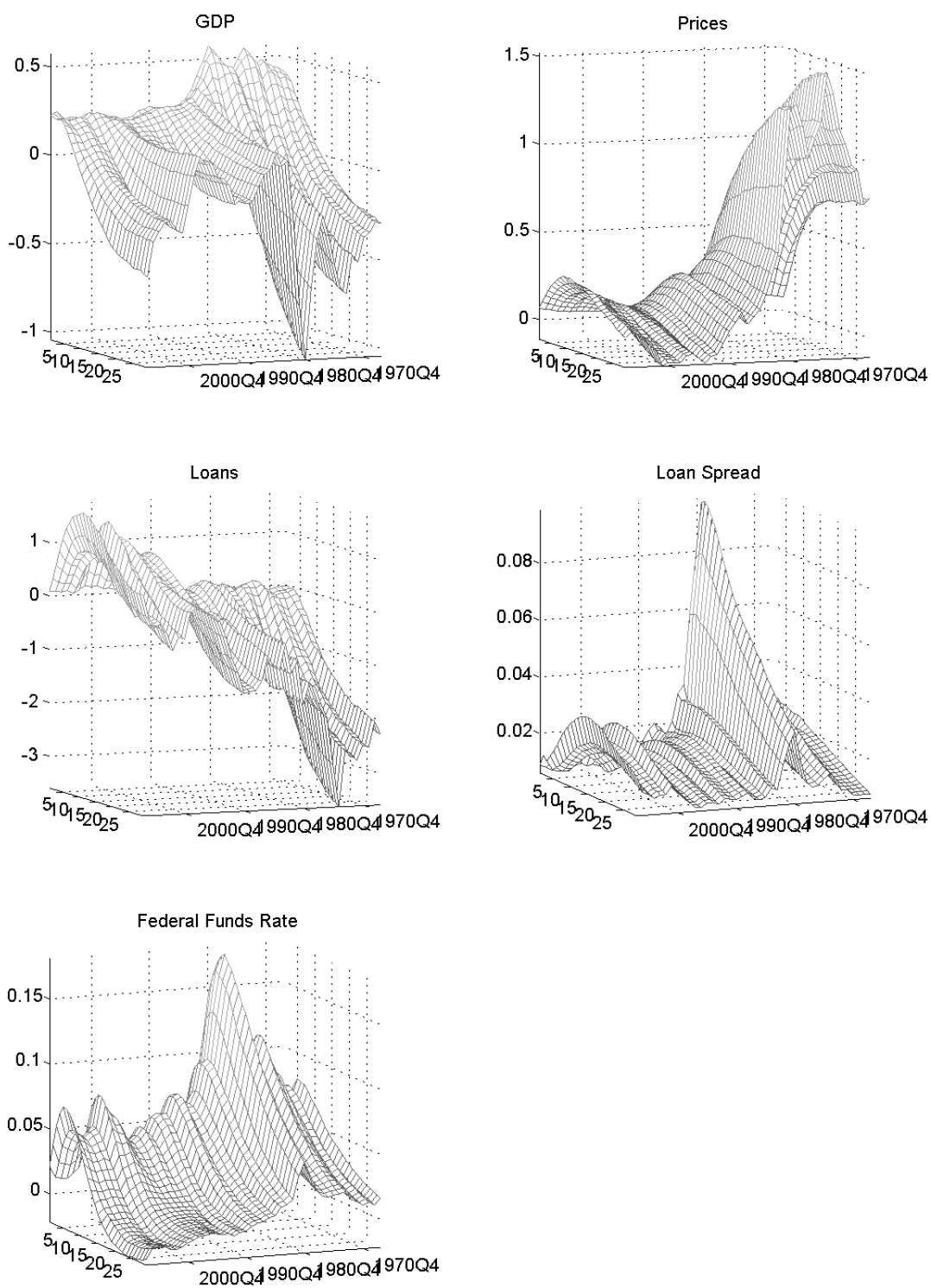


Figure 4.6: Impulse Response Functions to Demand Shocks - Selected Horizons

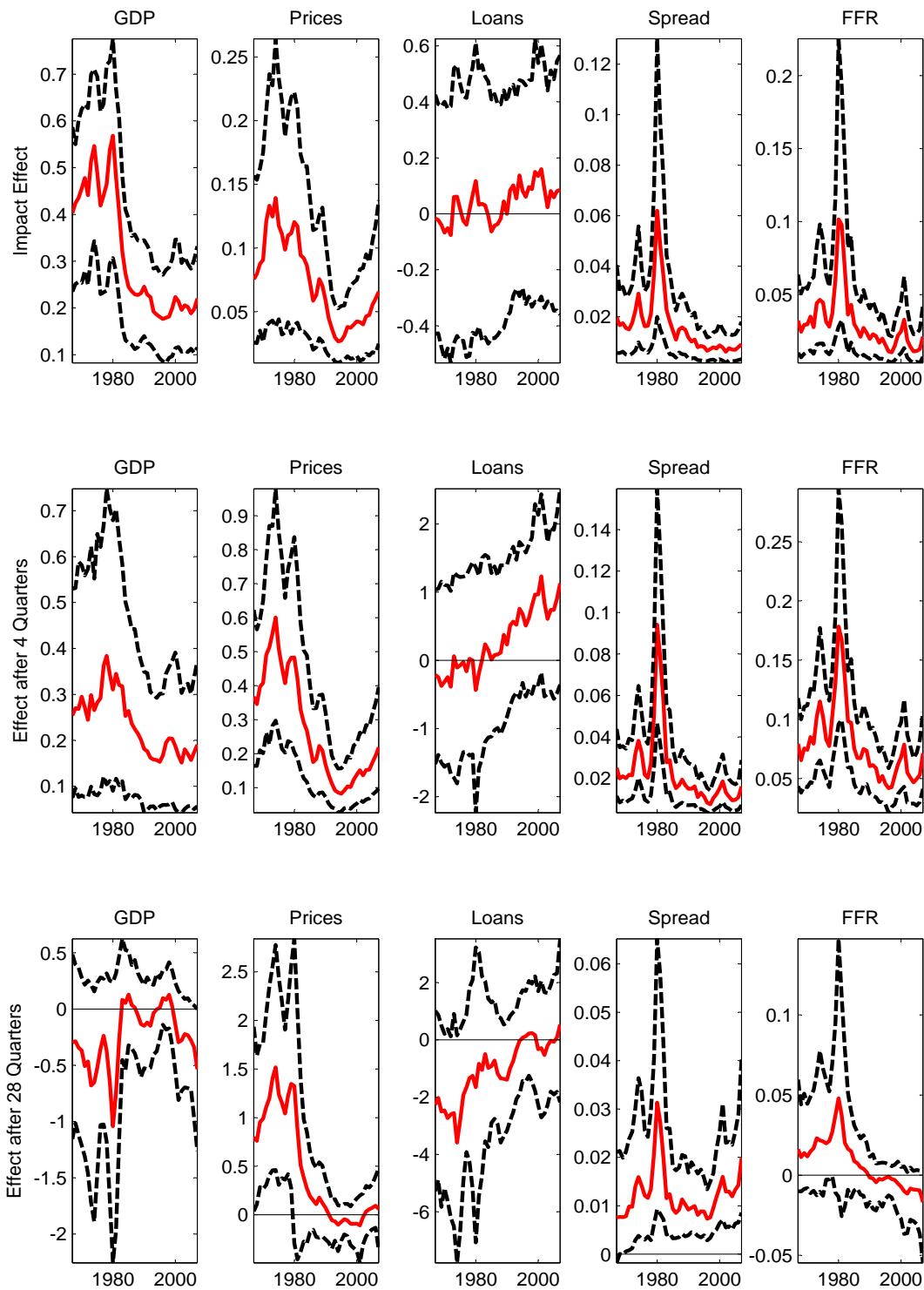
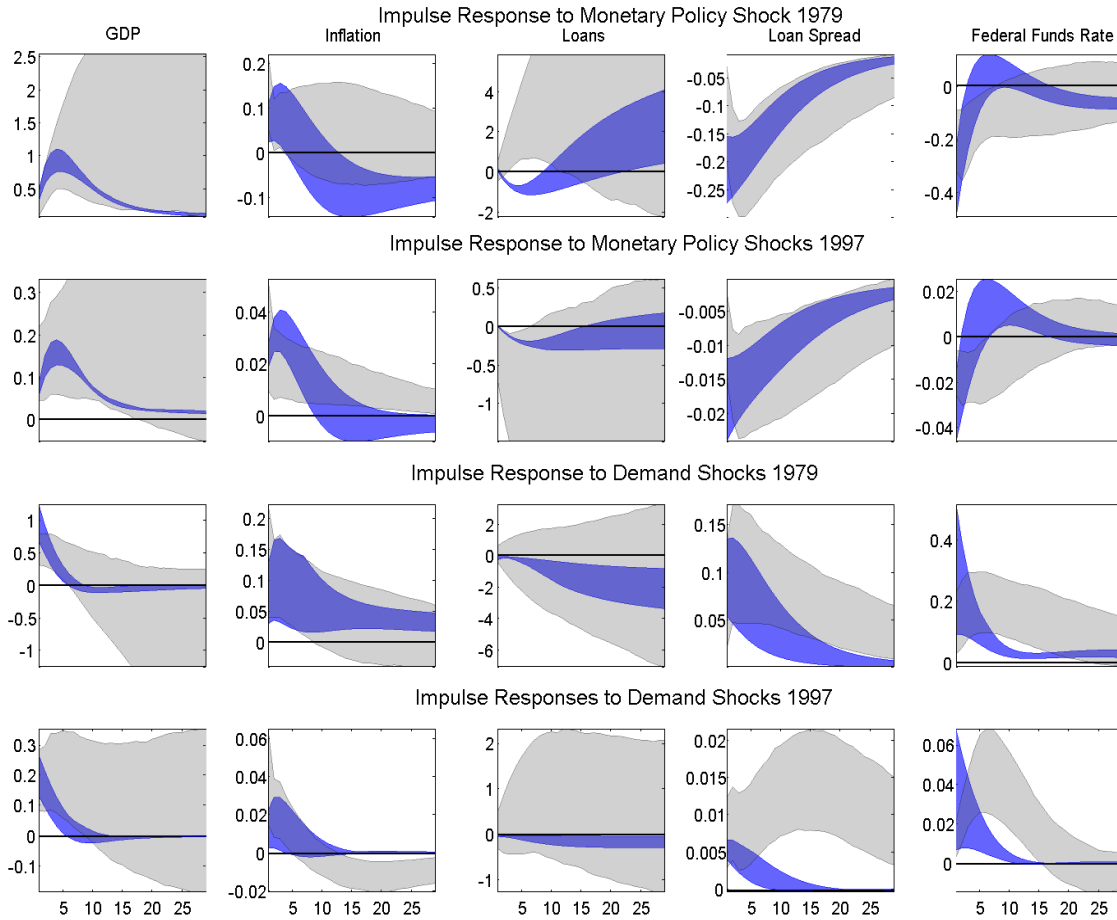
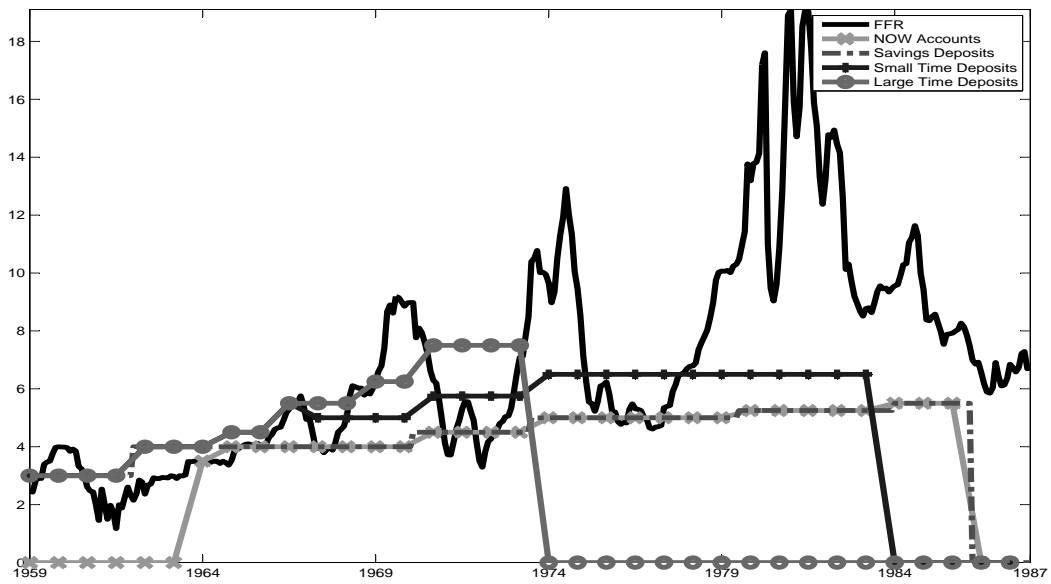


Figure 4.7: DSGE and VAR Impulse Response Functions



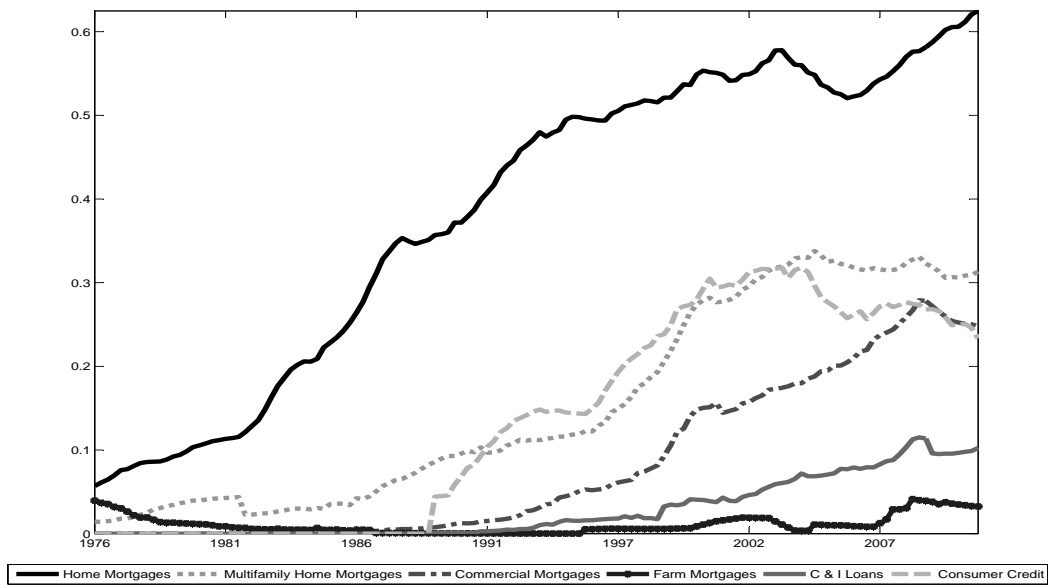
Notes: This figure shows the one standard deviation probability bands of the impulse responses of the TVP-VAR (gray shaded area) to monetary policy and demand shocks together with the one standard deviation probability bands of the impulse responses of the DSGE model (blue shaded area) for the estimated parameters reported in Table 3

Figure 4.8: Binding Deposit Rates



This Figure shows the effective Federal Funds Rate alongside the regulatory deposit rate ceilings for different classes of deposit accounts for the period 1959 to 1987. The data on the deposit rate ceiling is taken from the dataset accompanying Mertens (2008)

Figure 4.9: Securitization of Loans



This Figure shows for different loan categories the percentage of loans securitized relative to total loans outstanding for the period 1976 to 2009. The data on loan securitization is taken from the dataset accompanying Loutskina (2011).