Time Variation in Macro-Financial Linkages∗

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Abstract

We analyze macro-financial linkages in the US based on a Bayesian VAR model 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). We assess the contribution 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 also compare the results with those from a more commonly used constant parameter VAR and a time-varying parameter VAR where credit spreads, house price inflation and stock price inflation are replaced by a latent factor summarizing lots of financial variables. Our main findings are: (i) Financial sector shocks systematically affect the real economy during recessions, but not during booms. Such asymmetries cannot be captured by a constant parameter model. (ii) The contribution of financial shocks to the forecast error variance of GDP growth fluctuates considerably over time, from about 20 percent in normal times to 50 percent over the global financial crisis period. (iii) The Great Recession and the subsequent weak recovery can largely be traced back to negative house price shocks.

JEL classification: C32, E5, E3, C32

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1 Introduction

The Great Recession in 2008-2009 was triggered by major turbulences on financial markets: asset prices collapsed, volatility heightened and risk spreads widened. None of the macroeconomic models commonly used in academic research and in policy institutions was able to predict the strong economic downturn following these financial turmoils. Two main shortcomings of the standard macro modeling approach have recently been identified: the lack of financial variables in these models and the lack of a time-varying relationship between financial and macroeconomic variables.\(^1\) Our aim is to alleviate these shortcomings.

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 continuous changes in the autoregressive coefficients and stochastic volatilities.

Based on our estimated time-varying parameter VAR model (TV-VAR), we carry out a historical decomposition. We look at 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. We shed light on the underlying sources of time variation. We assess the contribution of unexpected changes in individual financial variables to GDP growth over time and look at possible changes in the volatility of financial shocks and in their impact on GDP growth. 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, a latent factor extracted from a very large number of financial variables.

\(^1\)The Vice Chairman of the Federal Reserve Donald L. Kohn argued in 2009 at the Federal Reserve Conference on Key Developments in Monetary Policy: "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 identifies ":[...] the need for models to take much better account of nonlinearties and tail events [...]". 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.

\(^2\)The 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.
Our analysis reveals the following main findings:

- Financial sector shocks systematically affect real economic activity only in recessions. In most boom periods financial sector shocks make no statistically significant contribution.

- The contribution of financial shocks to the forecast error variance of GDP growth fluctuates considerably over time, from around 20 percent over most of the sample period to roughly 50 percent over the Great Recession period.

- The main financial drivers of the Great Recession were shocks to house prices which account for about 2/3 of the overall contribution of the financial sector to GDP growth. The remaining contribution is most likely due to credit spread shocks.

- Our model attributes the weak economic recovery after the Great Recession to negative financial shocks. We show that this result can also be replicated by a VAR with constant parameters which accounts for a larger number of financial variables, including "non-classical" ones.

- We find significant changes in the volatility and the transmission of financial shocks to GDP growth over time. The most recent crisis period is characterized by particularly large house price and credit spread shocks and a relatively strong propagation of these two shocks to the real economy.

- The contribution of financial sector shocks implied by the C-VAR, the baseline TV-VAR and the TV-VAR which includes the NFCI are generally remarkably similar, especially from 1985 to 2002.

- The constant parameter model, however, consistently overestimates the positive contribution of financial sector shocks over several boom periods (1976-1979, 2003-2006 and after 2009). This suggests that the C-VAR cannot capture asymmetries in the transmission mechanism of financial shocks to the real economy (i.e. effects of negative shocks that are stronger in absolute terms than those of positive shocks).

Much of the previous work which models the interaction between the financial sector and the macroeconomy assumes constancy in the parameters.\textsuperscript{3} There are, however, theoretical reasons why the relationship between the financial sector and the macroeconomy and the linkages between different financial variables may be varying over time. There

\textsuperscript{3}Some authors have used standard macroeconomic VARs augmented with one or two additional financial indicators (e.g. Bjoernland and Jacobsen (forthcoming), Bjoernland and Leitemo (2009), Furlanetto, Ravazzolo and Sarfraz (2012), Peersman (2012), Jarocinski and Smets (2008)). Others construct Financial Conditions Indices (FCIs) as 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 models with constant parameters. Goodhart and Hofmann (2001) or Gauthier et al. (2004) acknowledge that this assumption may be problematic.
are gradual, long-lasting changes in the structural relationships between financial markets and the real economy. Financial innovation, globalization, regulatory changes on financial markets, and changes in the conduct of monetary policy can all alter the transmission of financial shocks to the macroeconomy. Finally, the transmission of financial shocks may differ in crisis periods because agency problems between lenders and borrowers are more pronounced in these periods and can amplify the effects of shocks on the real economy. 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 (known as the “financial accelerator”) (Bernanke, Gertler and Gilchrist (1999)). Moreover, 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)). In addition, the zero lower bound of nominal interest rates basically hit by monetary policy since 2008 and the subsequent measures of unconventional monetary policy may have affected the transmission of shocks. Finally, it is plausible to assume that, in crisis periods, financial shocks hit a particularly large number of financial market segments and financial intermediaries at the same time or that credit defaults multiply. In small time series models which permit changes in the size of shocks, this will be reflected in larger shocks.

There is a growing, but still small, recent 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, but not all 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 financial shock. An overview of previous work (including work for countries other than the US) is presented in Table 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 volatility of financial shocks is changing over time. This finding is also consistent with Stock and Watson (forthcoming) who focus on and systematically analyze the sources of the Great Recession in the US. They find that

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3Lenders’ risk aversion and greater uncertainty are additional amplifying elements during crises. See Hollo, Kremer and Lo Duca (2012).
relatively large shocks rather than a changed 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.

Compared to the literature surveyed above our approach has two desirable features. First, our time-varying parameter model is relatively flexible compared to some of the previous time-varying parameter models used in the above mentioned literature. The changing autoregressive coefficients capture possible time variation in the propagation of shocks, while the changing innovation covariance matrix picks up changes in both shock sizes and simultaneous relations among the variables. The data determine whether any observed time variation is due to changes in the shock size or in the transmission mechanism.

Second, the financial variables we include in our model capture the most relevant features of the financial sector\(^5\), and are closely related to key concepts in DSGE models with financial frictions. 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 \(\text{via}\) borrowing constraints (e.g. Iacoviello (2005), Iacoviello and Neri (2010)).\(^6\) 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 (see e.g. De Graeve (2008)). Furthermore, credit spreads give a reasonable description of problems associated with the financial intermediation process (Gilchrist and Zakrajeck (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 Zakrajeck (2012), Gilchrist and Zakrajeck (2012)).

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" or "financial distress", concentrating on a few key financial

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\(^5\)The VAR-based FCI papers which aim at assessing the importance of "financial conditions" for the macroeconomy listed above include similar variables (e.g. Beaton et al. (2009), Goodhart and Hofmann (2001), Gauthier et al. (2004), Swiston (2008), Guichard and Turner (2008), Guichard et al. (2009)).

\(^6\)The importance of house prices has, only, recently again attracted attention from economists. Iacoviello (2010) argues: "One of the key shifts of ideas has been the observation that movements in housing markets are not just the consequence of wider macroeconomic fluctuations, but also can be important impulses to business fluctuations." He cites Federal Reserve Chairman Ben S. Bernanke who stated in 2008 at a conference on Housing and Mortgage Markets: "Housing and housing finance played a central role in precipitating the current crisis."
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.

The remainder of the paper is organized as follows. In Section 2 we present the data, and in Section 3 the methodology. In Section 4, we provide results on the time-varying macro-financial linkages. First, we compute the reduced form correlations between financial variables and GDP growth implied by the TV-VAR. Next, 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 5 we summarize the main findings and conclude.

2 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. 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 index, the S&P 500 (monthly average), the Federal Funds rate and Moody’s BAA-AAA corporate bond spread.\(^7\)

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

\(^7\)A measure of real activity, inflation and the policy interest rate are also typically included in similar TV-VARs for the US economy (see, e.g., Cogley and Sargent (2005), Primiceri (2005)). To those we add the two asset prices and the credit spread.
R. Shiller’s webpage and used in Shiller (2005). The series are shown in Figure 1 (panels (a) and (b)).

As noted in the introduction, 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. The Federal Funds rate is mainly driven by monetary policy, and we will, in the remainder of the paper, look at financial shock contributions to real economic activity including and excluding the effects of monetary policy shocks.

3 Econometric methodology

3.1 The constant parameter VAR

The analysis departs from an \( \mu \)-dimensional vector \( \Phi_t \), which includes the macroeconomic variables \( \Re_t \) and the financial indicators \( \mathcal{F}_t \), \( \Phi_t \equiv (\Re_t, \mathcal{F}_t)' \). We assume that \( \Phi_t \) follows a VAR\((p)\) model.

\[
Y_t = C + B_1 Y_{t-1} + \ldots + B_p Y_{t-p} + u_t, \quad E(u_t) = 0, \quad E(u_t u_t') = R, \tag{3.1}
\]

\( t = 1, \ldots, T \), where \( C \) is an \( m \times 1 \) vector of intercepts, \( B_1, \ldots, B_p \) are the \( m \times m \) matrices of autoregressive VAR parameters and \( u_t \) denotes the \( m \times 1 \) vector of reduced form residuals, whose variance-covariance matrix is \( R \). Collecting the coefficients in the \( m \times (1 + mp) \) matrix \( B' = [C \ B_1 \ldots B_p] \) and defining the \( (1 + mp \times 1) \) vector \( X_t = [1, Y_{t-1}', \ldots, Y_{t-p}'] \), the VAR can be written more compactly as

\[
Y_t = B' X_t + u_t. \tag{3.2}
\]

An even more compact notation is

\[
Y = X B + u, \tag{3.3}
\]

where \( Y = [Y_1, \ldots, Y_T]' \), \( X = [X_1, \ldots, X_T]' \) and \( u = [u_1, \ldots, u_T]' \) 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 estimate this constant parameter VAR using Bayesian methods, assuming an independent Normal-Wishart prior:

\[
p(b, R^{-1}) = p(b)p(R^{-1})
\]
with  
\[ p(b) \sim N(\mu_b, \Sigma_b) \quad \text{and} \quad p(R^{-1}) \sim W(\bar{S}^{-1}, \nu), \]

where  
\[ b = \text{vec}(B). \]

Although the joint posterior distribution of the parameters of the model does not have a convenient form, it is possible to show that the conditional posterior distributions can be written as  
\[ b|Y, R^{-1} \sim N(\bar{b}, \bar{\Sigma}_b) \]

with  
\[ \bar{b} = \Omega_b^{-1}b + Z'(R^{-1} \otimes I_T)y \quad \text{and} \quad \bar{\Sigma}_b = (\Omega_b^{-1} + Z'(R^{-1} \otimes I_T)Z)^{-1} \]

where \( y = \text{vec}(Y) \) and \( Z = I_m \otimes X \).

The conditional posterior distribution for \( R^{-1} \) is given by  
\[ R^{-1}|Y, B \sim W(\bar{S}^{-1}, \bar{\nu}) \]

with  
\[ \bar{S} = S + (Y - XB)'(Y - XB) \quad \text{and} \quad \bar{\nu} = T + \nu. \]

We use a Gibbs sampler to simulate the joint distribution by sequentially drawing from the conditional distributions. To calibrate the prior hyperparameters 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 which will be discussed in the next subsection.

### 3.2 The time-varying parameter VAR

We now generalize the model and allow for time variation in the parameters in (3.1). Following, among others, Primiceri (2005), Benati (2008) and Baumeister and Peersman (2012), we assume that the parameters in (3.2) evolve according to a driftless random walk:  
\[ b_t = b_{t-1} + \eta_t, \]

with \( \eta_t \sim i.i.d. N(0, Q) \).
The reduced form innovations to the VAR system $u_t$ are zero mean normally distributed with a time-varying covariance matrix $R_t$, i.e. $u_t \sim N(0, R_t)$. We follow the standard practice introduced by Primiceri (2005) and assume that

$$u_t = A_t^{-1}H_t \epsilon_t,$$

(3.4)

where $\epsilon_t$ are the 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:

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

Both, the contemporaneous relations $a_{ij,t}$ and the innovations' volatilities $h_{ij,t}$ 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, $a_t = [a_{21,t}, a_{31,t}, a_{32,t}, \ldots, a_{65,t}]$.

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

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

where $I_6$ is a $6 \times 6$ 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. The prior distributions 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 prior distributions of the hyperparameters \( S, Q \) and \( Z \) are assumed to be distributed according to independent inverse-Wishart distributions. To calibrate the priors of the hyperparameters we use the corresponding OLS quantities calculated over a training sample which covers the first fifteen years of the data (60 quarters).

We assessed the convergence properties of the MCMC algorithm using inefficiency factors (IF) for the draws of states from the posterior distribution. The results, presented in Figure A.1 of the Appendix, show that all values of IF are well below 20, which is in general regarded as satisfactory (Primiceri (2005)).

3.3 Shock identification

To identify the financial shocks we carry out a Cholesky decomposition of the covariance matrix of the reduced form VAR residuals, see (3.4). 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 impose the restriction that macroeconomic variables react with a delay to financial shocks whereas financial variables can move instantaneously in response to macroeconomic shocks. This is a relatively standard assumption made in structural VAR studies (see, among others, Bernanke, Boivin and Eliasz (2005), Christiano, Eichenbaum and Evans (1999), Beaton et al. (2009), Buch, Eickmeier and Prieto (2010), Eichmeier and Hofmann (forthcoming)). The idea is that macroeconomic variables are slow moving and do not respond contemporaneously to developments in financial markets, while fast-moving financial variables are sensitive to contemporaneous macroeconomic shocks.

Separating macroeconomic and financial shocks using the recursive scheme is relatively straightforward and undisputed. The selected ordering is based on the rationale that wealth effects and effects which involve financial intermediaries are likely to reach the macroeconomy with a delay. Ordering macro variables before financial variables is also 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, why this is the case. Possible reasons are, as

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8 Since 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).
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\(^9\), which could be imposed to disentangle the various financial shocks from each other. For this reason we stick to the recursive scheme.\(^10\)

The consideration behind the chosen ordering within the financial block is that house prices are rather slow moving relative to interest rates or 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 et al. (2010)). Ordering the Federal Funds rate after credit spreads is consistent with Gilchrist and Zakrajsek (2012).

We will show below that results are very 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 can only give us a first tentative impression 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.

4 The time-varying macro-financial linkages

4.1 Reduced form correlations

In Figure 2 we report the time-varying contemporaneous correlations between the financial indicators and GDP growth implied by the TV-VAR. The estimates are based on the posterior distributions of the parameters derived from the TV-VAR. We present the medians together with the 16th and 84th percentiles.

Correlations between GDP growth and house and stock price inflation are estimated to be consistently positive and the correlation between GDP growth and the credit spread negative over the sample. The Federal Funds rate is negatively correlated with GDP growth until 1990; the correlation then turns insignificant. One interpretation of this result is that shocks which move the Federal Funds rate and GDP growth in different directions (such as monetary policy shocks or other shocks directly increasing funding

\(^9\)Credit supply shocks are perhaps an exception, although the few existing studies building DSGE models featuring a banking sector would not all imply the same identifying restrictions on key variables (see Eickmeier and Ng (2011) for a discussion).

\(^10\)We prefer not to use generalized impulse response functions (GIRFs) as other studies focusing on the effects of financial shocks on the real economy have done (e.g. Guichard and Turner (2008), Guichard et al. (2009), Gauthier et al. (2004), Ciccarelli et al. (2012)). It might be considered an advantage of the GIRF approach that impulse responses are not sensitive to the ordering of variables in the system. However, the GIRF approach delivers impulse responses to non-orthogonal shocks which are hard to interpret economically.
costs and dominating other effects) were mainly prevalent at the beginning of the sample, while shocks moving the two variables in the same direction (such as aggregate demand or asset price shocks which push both prices and economic activity in the same direction) were about equally important in the second half of the sample.

The correlation between house prices and GDP growth shows two large increases. These coincide with the final quarters of the housing booms 1976-1979 and 2001-2006, which were followed by the two longest and most severe recessions in post-WWII US history. This pattern accords well with the finding reported by Claessens, Kose and Terrones (2011) that recessions associated with house price busts (following the booms) tend to be longer and deeper than other recessions.

4.2 Results from the structural analysis

4.2.1 The overall contribution of financial sector shocks to GDP growth

We present in Figure 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. We present, again, the median together with the 16th and 84th percentiles.

Panel (a) reveals that financial sector shocks explain a large part of movements in GDP growth. The correlation of the median estimate of the sum of the contributions with GDP growth is at 0.6. In general, the contributions accord well with economic narratives. During all recessions included in our sample (indicated by the gray shaded areas) the financial shock contributions are negative, indicating that tight financial conditions depress economic activity during economic downturns. Financial conditions start to decline at least one year before the onset of a recession. Also in line with general economic wisdom and previous research (e.g. Hatzius, Hooper, Mishkin, Schoenholtz and Watson (2010), Beaton et al. (2009), Swiston (2008)) the financial shock contributions plummeted to record lows during the Great Recession, i.e. financial shocks explain a large part of the drop in economic activity in this period.

We also observe large positive contributions of financial shocks at the beginning of the sample period. These large contributions are mainly due to large 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 (i.e. contributions of the house price, credit spread and stock price shocks). We will discuss the role of monetary policy shocks in further detail below. After the Volcker Disinflation period (i.e. the mid-1980s), financial shocks contributed positively to GDP growth. These significantly positive effects of financial shocks to GDP growth do not disappear when shocks to the Federal Funds rate are excluded.
By contrast, from the 1990s onwards we basically find no significantly positive contributions of financial shocks. This suggests that during the last two decades positive financial shocks 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. Hatzius et al. (2010) argue that "non-classical" financial variables failed to improved after the crisis peak. Hence, 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. This explanation would also be consistent with Justiniano (2012), who argues that a DSGE model would require continuous adverse risk premium shocks to explain the struggling US economy, and with the view that economic recoveries after financial crises are typically slow and weak, as emphasized, for example, by Reinhart and Rogoff (2009)). Gali, Smets and Wouters (2012), using an estimated standard New Keynesian model, attribute the recent slow recovery to adverse demand and wage markup shocks. Their model does, however, not include financial frictions and intermediaries. Real world financial shocks would, in their model, therefore be reflected in macro shocks. Stock and Watson (forthcoming) yet hold another view. They show that trend output growth has gone down and attribute this decline to a weakening in labor force growth.

Our contribution series depicts 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 part, responsible for the weak recovery. We note that our model does not include "non-classical" financial variables, but can, instead, generate this result by allowing for time variation in the dynamics of a small set of "classical" financial variables. Apparently, the financial shocks in our time-varying parameter model are picking up parts of the movements in the "non-classical" variables. We will show below that the weakness of the recovery can largely be attributed to negative developments in the housing market.\footnote{To test whether trend growth has fallen, as argued by Stock and Watson (forthcoming), we also looked at the constant in the GDP growth equation of our TV-VAR but do not find a decline at the end of the sample.}

Figure 4(a) shows 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.\footnote{The share for the Great Recession is slightly smaller compared to the share explained by financial and uncertainty shocks found by Stock and Watson (forthcoming) of roughly 2/3. Their financial and uncertainty shocks are, however, not uncorrelated with other shocks.} The high share of variance explained in the 1970s is, however, entirely due
to large contributions of shocks to the Federal Funds rate, as shown in Figure 4(b) where we plot contributions of all financial shocks excluding monetary policy shocks.

In general, the story that emerges from the variance decomposition is that the share of variance 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, possibly due to financial frictions becoming more important in such periods. In the Great Recession in 2008/2009 the explanatory power of financial shocks for GDP growth variability is even significantly larger than in other recessions. Overall, this points to significant time variation in the propagation mechanism or the shocks’ size or both. We finally note that the variance decomposition results are remarkably similar to those for the US presented in Eickmeier et al. (2011b).

4.2.2 Contributions of individual financial shocks to GDP growth

**Historical and variance decompositions** Figure 5 shows the contributions of individual financial shocks to GDP growth estimated from the TV-VAR. Several findings are worthwhile emphasizing.

First, shocks to the policy interest rate were the most important drivers of the boom in the late 1970s and the recession in the early 1980s. 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 variance share of GDP growth attributable to monetary policy shocks is largest around the Volcker period, consistent with our findings. In order to bring inflation down, interest rates were strongly increased in the Volcker era since October 1979 at the cost of an economic recession which is also apparent from Figure 5.13

Second, the significantly positive contributions of the sum of all financial shocks in the mid-1980s found in Figure 3, are mainly due to credit spread shocks which contributed positively to GDP growth during the entire second half of the 1980s. The positive contributions of credit spread shocks accord well with the argument put forward, e.g., by Justiniano and Primiceri (2008), that regulatory changes in financial markets helped reducing financial frictions and led to expanded access to credit markets for households and firms, thereby boosting economic performance.14 Indeed, the regulatory reforms of the

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13 See also Coibion (2012) and Romer and Romer (2004) who argue that erratic monetary policy during this period played an important role for economic fluctuations.

14 Among the most important regulatory changes were the passing of the Depository Institutions Deregulation and Monetary Control Act (DIDMCA) in 1980. The DIDMCA increased deposit insurance from
early 1980s mark a transition from very high and volatile to much smaller risk spreads (see Figure 1(b)), which our model apparently attributes to positive credit spread shocks.

Third, our model can replicate what is nowadays conventional wisdom: the main drivers of the 2000/2001 recession were disturbances in the stock market reflecting the burst of the dot.com bubble, and the boom in the mid-2000s was mainly triggered by house price 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 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 attributable to the zero lower bound of nominal interest rates the Federal Reserve hit at the end of 2008. By contrast, 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 reduced the spread of (CDS-adjusted) Baa over Aaa bond yields by up to 61 basis points. Moreover, at the end of the sample, our model suggests that house price shocks still drag down GDP growth, which explains the overall negative contributions of financial shocks found in Figure 3.15

In Figure 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 period. Although the uncertainty surrounding these estimates is relatively large, the probability bands clearly show that the variance share explained by the house price shock in the most recent years exceeds significantly that in previous decades.16 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

$^{15}$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. This is consistent with our findings.

$^{16}$The average forecast error variance shares we find explained by house price shocks before the global financial crisis are broadly in line with those of Jarocinski and Smets (2008) explained by housing demand shocks of between 6 and 10 percent in the medium run. Their estimates are based on a constant parameter VAR estimated over 1987-2007.
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, in contrast, the stock market seems to have played a very limited role. We have already commented on the high variance share explained by shocks to the Federal Funds rate at the beginning of the sample. Figure 6 makes this point even more obvious, showing that the contribution of Federal Funds rate shocks in the 1970s and the early 1980s are significantly larger than in the subsequent decades. More recently, the contribution of monetary policy shocks is very low, consistent with other structural VAR (or FAVAR) studies (e.g. Jarocinski and Smets (2008), Eickmeier and Hofmann (forthcoming)).

4.2.3 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 real economic activity. 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 both.

Shock volatilities We start by presenting in Figure 7 the time-varying standard deviations of the orthogonalized financial shocks. The volatility of the shocks to house price inflation provides a dramatic illustration of the housing boom during the last decade, which was apparently accompanied by a drastic increase in the size of house prices shocks since 2000. The volatility of the stock price shocks has two peaks which occurred around the two major stock market crashes in 1987 and 2001. Our findings also suggest that the latest, particularly severe, recession was not associated with an increase in the size of stock price shocks. The volatility of credit spread shocks shows peaks around the five recessions and by far largest values over the global financial crisis period. The shocks to the Federal Funds rate are relatively high at the beginning of the sample, and much smaller peaks

17 The shock volatilities corresponding to the GDP growth and inflation equations are very similar to corresponding results presented elsewhere (see, among others, Benati and Mumentz (2007), Clark (2009) or Cogley, Primiceri and Sargent (2010)). The shock volatility of GDP growth has a downward trend between 1980 and the early-1990 which is illustrative for the transition period from the Great Inflation era to the Great Moderation era. The period from the mid-2000s to 2010 shows an increase of the shock volatility to levels which are, however, still much lower than at the beginning of the sample period. Similar to the findings in Clark (2009) the innovation volatility of inflation declines until the mid-1990s. From then on, the volatility increases again to reach at the end of the sample values similar to those in the 1980s. We do not show volatilities of shocks to GDP growth and inflation in the paper but make them available upon request. We also looked at the reduced form innovations’ standard deviations. They closely resemble the structural shock volatilities.
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)). We note 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.

To conclude, there is a substantial and significant amount of time variation. It is also striking how similar Figures 6 and 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, being in line with basically all previous time series studies reviewed in the introduction, strongly supports our strategy to take time variation in the shock volatilities into account.

**Impulse response functions** In Figure 8 we present median impulse responses 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 and are broadly in line with existing findings (see, e.g., Beaton et al. (2009)). 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 effects of house price shocks can possibly be explained by wealth effects being larger for housing wealth than for financial wealth as found, e.g., by Case et al. (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 9 impulse responses averaged over selected periods of time, and in Figure 10 we show differences between these periods.\(^{18}\) We first compare in panels (a) financial crisis and non-crisis periods to evaluate asymmetries in the transmission of financial shocks over the financial cycle. 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"),

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\(^{18}\)Specifically, 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 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.
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 and shaded in gray in previous figures.

Panels (a) of Figures 9 and 10 suggest that during the two stock market crashes and the 1988-1991 crisis, the transmission of any 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 which are, however, 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. There are three possible explanations. The particularly strong transmission during the latest crisis could either be due to the specific nature of the latest crisis or to monetary policy having hit the zero lower bound and undertaken unconventional measures. Our finding can, however, possibly also be explained by 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. We can, however, not distinguish between these three explanations.

In panels (b) of Figures 9 and 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 8 (but not from Figures 9 and 10), in the last decade, 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) 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

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19 See Lopez-Salido and Nelson (2010) for details on characteristics of the individual financial crises.
(2010) according to whom housing preference shocks have larger effects on GDP when collateral effects are taken into account.\textsuperscript{20} They are also consistent with Eickmeier and Hofmann (forthcoming) who have emphasized 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 et al. (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 do not seem to have changed, but the overshooting (i.e. the positive effects in the medium term) has become significantly smaller. The charts also suggest that the effects of stock price shocks have become significantly larger in the 1990s and 2000s compared to the 1970s and the 1980s. This is fully 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 literature analyzing the changing transmission of monetary policy shocks on output in Table 4 of Eickmeier, Lemke and Marcellino (2011a)).

Interestingly, 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 et al. (2000)) and with the TV-VAR evidence by Korobilis (2012).

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 parameter time variation do no find evidence for time variation in the transmission.\textsuperscript{21}

\textsuperscript{20} They 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 GDP 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.

\textsuperscript{21} It 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.
5 Alternative models

In this section we compare the main outcomes of our baseline TV-VAR with the results from a constant parameter VAR (C-VAR) as described in Section 3.1 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 include the growth of the volume of credit in our baseline model.

Comparison with a C-VAR The C-VAR contains the same variables as the TV-VAR and is estimated over the same sample period. Figure 11 shows the overall contributions of financial sector shocks while Figure 12 presents the contributions of financial sector shocks excluding monetary 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 11 presents the median overall contributions implied by the C-VAR alongside with the 16th and 84th percentiles. The graphs reveal that 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. The correlation of the C-VAR contribution series with GDP growth is also reasonably high (0.5), although a bit lower than the correlation of the contribution series with GDP growth from the baseline TV-VAR (about 0.6).

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. Given that both models imply very similar contributions of financial shocks to GDP growth in other periods, including recessions, this might point 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 finding implied by the C-VAR confirms that time variation in the parameters is needed to attribute the weak economic recovery the negative financial shock influences.

22Given 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.
In the Appendix (Figures A.10 and A.11) we show some results for individual financial shocks obtained from the C-VAR. House price shocks make relatively strong positive contributions which the TV-VAR does not find. This result from our baseline TV-VAR is in line with Guerrieri and Iacoviello (2012) who find, based on an asymmetric VAR, on panel regressions and on a DSGE model à la Iacoviello and Neri (2010), that negative house price shocks have larger (negative) effects on economic activity when borrowing constraints become binding and collateral effects large than positive house price shocks which lead to a relaxation of collateral constraints. It is also in line with Case et al. (2013) who find that positive housing wealth effects from house price increases are significantly smaller than negative ones from house price declines. This is attributed to home sellers behaving differently according to Kahneman and Tversky’s prospect theory. Moreover, monetary policy shocks are estimated by the C-VAR to make smaller contributions at the beginning of the sample. Impulse response functions obtained from the C-VAR are very similar to those obtained from the TV-VAR averaged over the entire sample period.

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 and presented in Figure 1 (c). The NFCI is constructed as the first latent factor extracted from an unbalanced panel of 100 financial indicators. The financial indicators cover money markets (28 indicators including interest rate spreads, implied volatility and trading volumes), debt and equity markets (27 indicators including equity and bond price measures capturing volatility and risk premiums, real estate prices, asset-backed security) and the banking system (45 indicators including survey-based measures of credit availability, accounting-based measures for commercial banks and shadow banks and interest rate spreads). Importantly, the NFCI also takes into account series capturing "non-classical" financial segments, which have only become important recently. Hence, those series start only in the 1990s or the 2000s. 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. We

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23 Case et al. (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).
note that the NFCI is only published since 1973. We therefore estimate the model over 1973-2012 and use 1973-1984 as our training sample.24 25

Figure 11, panels (a) and (c), shows 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 12 show the contributions of all financial sector shocks excluding shocks to the Federal Funds rate (i.e. of only shocks to the NFCI). The evolutions of the financial sector shock contributions from the baseline TV-VAR and the TV-VAR which includes the NFCI are quite similar. The correlation of the contribution from the alternative TV-VAR with GDP growth is somewhat lower (0.5) than from the baseline model. The NFCI model suggests slightly less negative contributions over recession periods. Moreover, no significant positive contributions of financial shocks to GDP growth are found, which is similar to the finding from the baseline TV-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 5 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 which is worth 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 our finding from our baseline that financial sector shocks are still influencing the growth in the US negatively. As an additional check we re-estimated 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. We make these results available upon request.

We therefore conclude that 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 et al. (2010), or by allowing for time variation in the parameters in a VAR with a few standard key financial variables. We also note that a simple linear combination of financial variables is, by itself, only of minor help in assessing the stance of financial market conditions, i.e. the role financial markets play for the real

24 For 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.

25 The 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.
economy. Instead the financial variables need to be related to some target variable (GDP growth in our case).

**Further robustness checks** We carry out further robustness checks. First, we consider two alternative orderings for the financial variables in the baseline TV-VAR. One is: house price inflation → Federal Funds rate → credit spread → stock price inflation. That ordering within the financial block is similar to the one chosen by Beaton et al. (2009). The assumption that the Federal Funds rate responds with a delay to shocks to credit spreads and the stock market is also consistent with Swiston (2008) who argues that monetary policy decisions are, in general, only taken every six weeks. The other ordering we consider is: house price inflation → stock price inflation → credit spread → Federal Funds rate, i.e. we switch the ordering between stock price inflation and the credit spread.

Figures A.2-A.9 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 A.6). 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 (Figure 1(b)). On the one hand, we find stock price shocks’ standard deviations to look less plausible with this alternative ordering compared to the baseline ordering (Figure A.8). 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 disentangle (in particular stock price and credit spread) shocks.

As a second robustness check, we introduce real total business credit growth in our baseline TV-VAR. This is in order to assess whether the main results obtained so far are influenced by the fact that we omit the volume of credit from our baseline model and that we only use credit spreads to capture the credit market. 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.

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The correlation between the residuals of the credit spread and stock price equations (based on the median estimates) equals -0.83 when calculated over 2007Q2-2012Q2. By contrast, this correlation is only at -0.07 when calculated over 1973Q2-2007Q1.

Helbling, 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.

Using overall credit or corporate bonds, which are even more closely linked to the corporate bond spreads, instead of total business credits yields very similar results.
Figure A.12 reveals that 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.

Figures A.13-A.16 provide more detailed results. The contribution of credit growth shocks to the forecast error variance of GDP growth is very small over the entire sample period, never exceeding 6 percent (median estimate). Credit growth shocks display a positive transitory effect on GDP growth. We also find that there is not much variation over time in the transmission nor in the volatility of the shocks.

The historical decomposition of GDP growth is also not much affected by including credit growth in the model. We detect some negative contributions from credit growth shocks around the LDC Debt Crisis in the early 1980s. In the early period of the sample, the introduction of credit growth shocks in the model slightly reduces the contribution of monetary policy shocks. We also find positive contributions in the run-up to the dot.com bubble, which has been associated with an increase in business credit, and negative contributions around the burst of that bubble. At the end of the sample, credit growth shocks make small positive contributions, probably due to the recovery of credit markets after unconventional monetary policy measures. Overall, we can, however, conclude that the introduction of credit growth in the model leaves our main results unaffected.

6 Conclusions

In this paper we have analyzed the macro-financial linkages in the US based on a Bayesian VAR model 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). Our model therefore has two important features which 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 a latent factor summarizing a very large number of financial variables.

Our main findings are: (i) Financial sector shocks systematically affect the real economy mainly during recessions, but not during booms. Such asymmetries cannot be captured by a constant parameter model. (ii) The contribution of financial shocks to the forecast error variance of GDP growth fluctuates considerably over time, from about 20 percent in some periods to roughly 50 percent over the global financial crisis period. (iii) The Great Recession and the subsequent weak recovery can largely be traced back to house price shocks.
References


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**URL:** http://ideas.repec.org/p/bca/bocawp/04-22.html


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Reinhart, C. and Rogoff, K. (2009), *This time is different: eight centuries of financial folly*, Princeton University Press.


Table 1: Overview on the empirical literature on time-varying macro-financial linkages

<table>
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<th>Study</th>
<th>Model</th>
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<th>Time variation</th>
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<td>Eickmeier et al. (2011)</td>
<td>FAVAR (10 latent and observed factors)</td>
<td>Coefficients, shock vola</td>
<td>Smooth</td>
<td>US financial conditions index</td>
<td>Recursive</td>
<td>1971-2009 9 advanced countries</td>
<td></td>
<td>Gradual increase of the transmission over time, shock size bigger in financial crises.</td>
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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 1: Time series plots

(a) Macroeconomic series

(b) Observable financial series

(c) NFCI from the Federal Reserve Bank of Chicago
Figure 2: Unconditional correlations with GDP growth estimated from the TV-VAR (median estimates and 1 standard deviation percentiles)

Notes: Grey shaded areas indicate recession dates according to the NBER recession dating committee.
Figure 3: Overall contribution of financial shocks estimated from the TV-VAR (median and 1 standard deviation percentiles)

(a) Including shocks to the Federal Funds rate

(b) Excluding shocks to the Federal Funds rate

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 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)

(a) Including shocks to the Federal Funds rate

(b) Excluding shocks to the Federal Funds rate
Figure 5: Contributions of individual financial shocks estimated from the TV-VAR (median estimates)

Notes: see notes to Figure 3.

Figure 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 7: Standard deviations of structural shocks estimated from the TV-VAR (median estimates and 1 standard deviation percentiles)
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Figure 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)

(a) Financial crisis vs. non-crisis periods

(b) Non-crisis periods
Figure 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)

(a) Financial crisis vs. non-crisis periods

(b) Non-crisis periods
Figure 11: Overall contribution of financial shocks

(a) Median estimates

(b) C-VAR
(c) TV-VAR with FCI

Notes: Black: all shocks, Panel (a): red: derived from TV-VAR; green: C-VAR; blue: TV-FCI-VAR (starting in 1984Q3), Panels (b) and (c): solid red: median; dashed red: 16th and 84th percentiles. See also notes to Figure 3 for more information.
Figure 12: Overall contribution of financial shocks excluding shocks to the Federal Funds rate

(a) Median estimates

(b) C-VAR
(c) TV-VAR with FCI

Notes: Black: all shocks, Panel (a): red: derived from TV-VAR; green: C-VAR; blue: TV-FCI-VAR (starting in 1984Q3), Panels (b) and (c): solid red: median; dashed red: 16th and 84th percentiles. See also notes to Figure 3 for more information.
Appendix

Figure A.1: Results of test for convergence of the hyperparameters and the states
Figure A.2: Contributions of individual financial shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation → Federal Funds rate → credit spread → stock price inflation (median estimates).

Notes: see notes to Figure 3.
Figure A.3: 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 → Federal Funds rate → credit spread → stock price inflation (median estimates and 1 standard deviation percentiles)
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Figure A.6: Contributions of individual financial shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation → stock price inflation → credit spread → Federal Funds rate

Notes: see notes to Figure 3.

Figure A.7: 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 → stock price inflation → credit spread → Federal Funds rate (median estimates and 1 standard deviation percentiles)
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Figure A.11: Contributions of individual financial shocks from the C-VAR (median estimates)

Notes: see notes to Figure 3.
Figure A.12: Overall contribution of financial shocks – TV-VAR including credit growth

Notes: Black: all shocks, solid red: median; dashed red: 16th and 84th percentiles. See also notes to Figure 3 for more information.

Figure A.13: Contributions of individual financial shocks estimated from the TV-VAR where credit growth is included and the ordering in the financial block is: house price inflation → credit growth → credit spread → stock price inflation → Federal Funds rate

Notes: see notes to Figure 3.
Figure A.14: Forecast error variance shares of GDP growth at the 5-year horizon explained by individual financial shocks estimated from the TV-VAR where credit growth is included and the ordering in the financial block is: house price inflation → credit growth → credit spread → stock price inflation → Federal Funds rate (median estimates and 1 standard deviation percentiles)

Figure A.15: Standard deviations of structural shocks estimated from the TV-VAR where credit growth is included and the ordering in the financial block is: house price inflation → credit growth → credit spread → stock price inflation → Federal Funds rate (median estimates and 1 standard deviation percentiles)
Figure A.16: Impulse responses of GDP growth to unit financial shocks estimated from the TV-VAR where credit growth is included and the ordering in the financial block is: house price inflation → credit growth → credit spread → stock price inflation → Federal Funds rate (median estimates).