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Time variation in macro-financial linkages

Esteban Prieto
(University of Tuebingen)

Sandra Eickmeier
(Deutsche Bundesbank)

Massimiliano Marcellino
(European University Institute, Bocconi University and CEPR)

Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-0

Please address all orders in writing to: Deutsche Bundesbank,
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Non-technical summary

None of the macroeconomic models commonly used in academic research and in policy institutions was able to predict the strong economic downturn following the Global Financial Crisis. Two main shortcomings of the standard macro modeling approach have been identified: the lack of financial variables in these models and the lack of a time-varying relationship between financial and macroeconomic variables.

We try to overcome these shortcomings and 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. In order to account for possible time variation in the relationship between financial indicators and the macroeconomy, we allow for continuous changes in the autoregressive coefficients, contemporaneous relations and stochastic volatilities. This reflects the fact that time variation in the shock transmission can occur because of permanent structural changes such as financial globalization, regulatory changes or changes in the conduct of monetary policy or because of temporary changes due to agency problems between lenders and borrowers which are more pronounced in financial crisis periods than in normal periods.

Based on our estimated time-varying parameter VAR, 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 then 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 model with those estimated from a constant parameter VAR and a VAR in which we replace the financial variables with the National Financial Conditions Index published by the Federal Reserve Bank of Chicago, a latent factor extracted from a very large number of financial variables.

Our main findings are: (i) 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 roughly 50 percent over the global financial crisis period. (ii) The Great Recession and the subsequent weak recovery can largely be traced back to negative housing shocks. (iii) Housing shocks have become more important for the real economy since the early-2000s, and negative housing shocks are more important than positive ones.

Nicht-technische Zusammenfassung

Keines der in der wissenschaftlichen Forschung und in wirtschaftspolitischen Institutionen gebräuchlichen makroökonomischen Modelle war in der Lage, den kräftigen Wirtschaftsabschwung im Gefolge der globalen Finanzkrise vorherzusagen. Es wurden im Wesentlichen zwei Schwachstellen in Bezug auf den Standardansatz für die makroökonomische Modellierung identifiziert: Die entsprechenden Modelle lassen finanzielle Variablen sowie eine sich im Zeitverlauf ändernde Beziehung zwischen finanziellen und makroökonomischen Variablen außer Acht.

Ausgehend davon integrieren wir einige wichtige Finanzindikatoren in ein üblicherweise verwendetes (Bayesianisches) makroökonomisches Vektor-autoregressives (VAR-) Modell für die Vereinigten Staaten. Dieses schätzen wir für den Zeitraum vom ersten Quartal 1958 bis zum zweiten Quartal 2012. Das VAR-Modell beinhaltet das BIP-Wachstum, die Veränderung des BIP-Deflators, die Entwicklung der Immobilienpreise, die Renditedifferenz von Unternehmensanleihen, die Aktienkursentwicklung und die Federal Funds Rate. Um einer möglichen Zeitvariation in der Beziehung zwischen Finanzmärkten und der Gesamtwirtschaft Rechnung zu tragen, werden kontinuierliche Veränderungen in den autoregressiven Koeffizienten, kontemporären Beziehungen der Variablen und Volatilitäten der Schocks berücksichtigt. Damit wird der Tatsache Ausdruck verliehen, dass permanente strukturelle Veränderungen – wie etwa die fortschreitende Finanzmarktintegration, regulatorische Anpassungen oder Änderungen in der Durchführung der Geldpolitik – sowie vorübergehende Veränderungen infolge von „Agency“-Problemen zwischen Kreditgebern und Kreditnehmern, die in Zeiten einer Finanzkrise stärker ausgeprägt sind als in normalen Phasen, zu Veränderungen der Übertragung von Schocks über die Zeit führen können.

Auf Basis des geschätzten VAR-Modells mit zeitvariablen Parametern wird die Summe der Beiträge der auf jeden einzelnen Finanzindikator wirkenden Schocks zum BIP-Wachstum als Messgröße herangezogen, um die allgemeine Bedeutung des Finanzsektors als Quelle von Schocks für die Gesamtwirtschaft zu ermitteln. Anschließend werden die zugrunde liegenden Ursachen der zeitlichen Variation beleuchtet. Dabei werden der Beitrag unerwarteter Veränderungen einzelner Finanzvariablen zum Wachstum des BIP im Zeitverlauf abgeschätzt und mögliche Veränderungen in der Volatilität finanzieller Schocks sowie in deren Auswirkungen auf das BIP-Wachstum untersucht. Abschließend werden die Beiträge von Finanzschocks, die anhand des beschriebenen Modells abgeschätzt wurden, mit jenen, die sich, alternativ, aus einem VAR mit konstanten Parametern ergeben sowie aus einem VAR, bei dem die wenigen einbezogenen Finanzvariablen durch den von der Federal Reserve Bank of Chicago veröffentlichten National Financial Conditions Index – einem aus einer Vielzahl finanzieller Variablen abgeleiteten unbeobachteten Faktor – ersetzt wurden.

Die wichtigsten Erkenntnisse lauten: a) Der Beitrag finanzieller Schocks zur Prognosefehlervarianz des BIP-Wachstums schwankt im Zeitverlauf erheblich und reicht von etwa 20 % in „normalen“ Phasen bis hin zu rund 50 % während der globalen Finanzkrise. b) Die „Große Rezession“ und die in der Folgezeit nur schwach ausgeprägte Erholung lassen sich weitgehend auf negative Schocks im Immobiliensektor zurückführen. c) Derartige

Schocks im Immobiliensektor haben seit Beginn der 2000er Jahre an Bedeutung für die Realwirtschaft gewonnen, und negative Immobiliensektorschocks übertragen sich stärker als positive.

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Time Variation in Macro-Financial Linkages*

Esteban Prieto[†] Sandra Eickmeier[‡] Massimiliano Marcellino[§]

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Abstract

We analyze the contribution of credit spread, house and stock price shocks to GDP growth in the US based on a Bayesian VAR with time-varying parameters estimated over 1958-2012. Our main findings are: (i) The contribution of financial shocks to GDP growth fluctuates from about 20 percent in normal times to 50 percent during the global financial crisis. (ii) The Great Recession and the subsequent weak recovery can largely be traced back to negative housing shocks. (iii) Housing shocks have become more important for the real economy since the early-2000s, and negative housing shocks are more important than positive ones.

JEL classification: C32, E5, E3

Keywords: Financial shocks, time-varying parameter VAR model, Global Financial Crisis, macro-financial linkages.

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[†]esteban.prieto@wiwi.uni-tuebingen.de, University of Tuebingen

[‡]sandra.eickmeier@bundesbank.de, Deutsche Bundesbank

[§]massimiliano.marcellino@eui.eu, European University Institute, Bocconi University and CEPR

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 predict the strong economic downturn following these turmoils. Two main shortcomings of the standard macro modeling approach have recently been identified: the lack or insufficient modelling 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 nonlinearties and tail events [...]".[1]

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 continuous (random walk) 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 model (TV-VAR), 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

[1] Similarly, 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.

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, a latent factor extracted from a very large number of financial variables.

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. 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. 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 parmeter 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 2 we relate our paper to the literature and discuss our original contributions. In Section 3 we present the data, and in Section 4 the methodology. In Section 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 6 we summarize the main findings and conclude.

2 Related literature and features of our approach

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 (2011*b*), 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 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, possibly reflecting that in financial 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. 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 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. Finally, our paper is related to recent empirical evidence by Del Negro and Schorfheide (2013) supporting that financial variables and frictions may matter more over financial crisis periods than in normal times. The authors show that a DSGE model with financial frictions and credit risk spreads delivers better out-of-sample macroeconomic forecasts than a DSGE model without these features since 2008, whereas over most of the rest of their sample period (starting in 1994) the simple model without financial frictions and credit risks yielded better forecasts.

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 time-varying specifications used in the surveyed literature. The changing autoregressive coefficients capture possible time variation in the propagation of shocks, while the 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, for example, to financial innovation, globalization or regulatory changes on financial markets. In addition, the model can capture asymmetries in the real 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 (known as the "financial accelerator") (Bernanke, Gertler and Gilchrist (1999)).[3] Our model can also account for possible changes in the financial shock transmission due to an altered conduct of monetary policy or the zero lower bound of nominal interest rates basically hit by monetary policy since 2008 and the subsequent measures of unconventional monetary policy.

Second, the financial variables we include in our model cover the most relevant features of the financial sector[4], 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 *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 (see e.g. De Graeve (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

[3] 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)). Lenders' risk aversion and greater uncertainty are additional amplifying elements during crises. See Hollo, Kremer and Lo Duca (2012).

[4] VAR-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)).

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" or "financial distress", 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 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 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 1 (panels (a) and (b)).

We assume that the financial variables we include capture developments in the financial

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

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).

4 Econometric methodology

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:

$$Y_t = C_t + \mathcal{B}_{1t} Y_{t-1} + \ldots + \mathcal{B}_{pt} Y_{t-p} + u_t, \quad E(u_t) = 0,\ E(u_t u_t') = R_t, \tag{4.1}$$

$t = 1, ..., T$, where for each t C_t is an $m \times 1$ vector of intercepts, $\mathcal{B}_{1t}, ..., \mathcal{B}_{pt}$ 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 $B_t' = [C_t\ \mathcal{B}_{1t} \ldots \mathcal{B}_{pt}]$ 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

$$Y_t = B_t' X_t + u_t. \tag{4.2}$$

An even more compact notation is

$$Y = X\, B_t + u, \tag{4.3}$$

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

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

with $\eta_t \sim i.i.d.N(0, Q)$.

Moreover, we have:

$$u_t = A_t^{-1} H_t \epsilon_t, \tag{4.4}$$

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:

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

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, $a_t = [a_{21,t}, a_{31,t}, a_{32,t}, ..., a_{65,t}]'$.

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 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

[6] 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).

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 compare in Figure A.1 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 A.2, show that all values of IF are well below 20, which is typically regarded as satisfactory (Primiceri (2005)).

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, see equation (4.4). We choose the following ordering: GDP growth → GDP deflator inflation → house price inflation → credit spread → stock price inflation → 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. It is a 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), 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[7], which could be imposed to disentangle the various financial shocks from each other. 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 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 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.

5 The time-varying macro-financial linkages

5.1 The overall contribution of financial sector shocks to GDP growth

We present in Figure 2 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 (i.e. the sum of the contributions of the house price, credit spread and stock price 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

[7]Even 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).

[8]This 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 et al. (2009), Goodhart and Hofmann (2001), Gauthier et al. (2004), Swiston (2008), Guichard and Turner (2008), Guichard et al. (2009)). All these studies use, however, models with constant parameters. Goodhart and Hofmann (2001) or Gauthier et al. (2004) acknowledge that this assumption may be problematic.

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.

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 preceeded 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]

[9]See 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

Other explanations for the slow and weak recovery not related to financial markets are proposed as well. 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) hold yet another view. They show that trend output growth has gone down in the latest crisis and attribute this decline to a weakening in labor force growth. Based on a VAR model with time-varying shock volatilities, Benati (2013) does not find that potential output growth in the US has been affected negatively over the Global Financial Crisis period, which contrasts somewhat the Stock and Watson (forthcoming) result.

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.[10]

Taking a medium-term perspective, Figure 3(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.[11] 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(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.

a substantial overhang of vacant homes.

[10] To test whether mean growth has fallen 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.

[11] 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.

5.2 Contributions of individual financial shocks to GDP growth

Figure 4 shows the contributions of individual financial shocks to GDP growth estimated from the TV-VAR. Several findings are worthwhile emphasizing.

First, the significantly positive contributions of the sum of all financial shocks in the mid-1980s found in Figure 2 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 (2008)).[12] Indeed, the regulatory reforms of the early-1980s mark a transition from very high and volatile to much smaller risk spreads (see Figure 1(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 et al. (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 attributable 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 reduced substantially 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 2. This finding is in line with Bordo and Haubrich (2012)'s explanation for the weak and slow recovery from the Great Recession and with Claessens and Kose (2013), who

[12] One 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)).

have discovered as a pattern for a large number of countries that the economy typically starts recovering from recessions before house prices have bottomed out.

In Figure 5 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 variance share explained by the house price shock in the most recent years exceeds significantly that in previous decades.[13] 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)).

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 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 to both.

[13] 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.

5.3.1 Shock volatilities

We start by presenting in Figure 6 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 5 and 6 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.

5.3.2 The role of changing dynamics

In Figure 7 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 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 8 impulse responses averaged over selected periods of time, and in Figure 9 we show differences between these periods.[14] We first compare in panels (a) financial crisis, as defined in the data section, and non-crisis periods to evaluate asymmetries in the transmission of financial shocks over the financial cycle. Panels (a) of Figures 8 and 9 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

[14] 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.

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, which could be 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.[15]

In panels (b) of Figures 8 and 9 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 7, 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) 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) according to whom housing preference shocks have larger effects on GDP when collateral effects are taken into account.[16] They are also consistent with Eickmeier and Hofmann

[15] We 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.

[16] 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.

(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 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 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 literature analyzing the changing transmission of monetary policy shocks on output 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 et al. (2000)) and with the TV-VAR evidence by Korobilis (2012).

Finally, in order to better understand the underlying sources the time variation in the impulse responses we show in Figure A.3 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 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 parameter time variation do no find evidence for time variation in the transmission.[17]

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.

[17] 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.

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.[18] [19] Figure 10 shows the overall contributions of financial sector shocks while Figure 11 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 10 presents the median overall contributions implied by the C-VAR alongside with 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 the negative financial shock influences.

In the Appendix (Figures A.4 and A.5) 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, based on an asymmetric VAR, on panel regressions and on a DSGE model, that negative house price shocks have larger (negative) effects on

[18] We 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.

[19] Given 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.

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 for psychological reasons after house price decreases than after increases according to Kahneman and Tversky's prospect theory.[20] 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.

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 and presented in Figure 1 (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.[21] Importantly, the NFCI also takes into account series capturing "non-classical" financial segments. Some of 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. The NFCI is only published since 1973. We therefore estimate the model over 1973-2012 and use 1973-1984 as our training sample.[22] [23]

Figure 10, panels (a) and (c), shows the sum of the contributions of all financial sector

[20] 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).

[21] The 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.

[22] 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.

[23] 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.

shocks to GDP growth (i.e. shocks to the NFCI and the Federal Funds rate), and panels (a) and (c) of Figure 11 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 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-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 4 (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 our finding from our baseline model that financial sector shocks are still influencing growth in the US negatively. As an additional check we re-estimate a constant parameter VAR with GDP growth, inflation, the NFCI and the Federal Funds rate and make results available upon request. 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 et al. (2010), or by allowing for time variation in the parameters in a VAR with a few standard key financial variables.

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 → Federal Funds rate → credit spread → 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 → stock price inflation → credit spread → Federal Funds rate, i.e. we switch the ordering between stock price inflation and the credit spread.

Figures A.6-A.13 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.10). 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 1(b) and A.3). On the one hand, stock price shocks' standard deviations look less plausible with this alternative ordering compared to the baseline ordering (Figure A.12). 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.[24] 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 in our baseline model. One could argue that only a physical cut-back in credit supply has major effects on the economy.[25] 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 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

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

[25] 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.

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)), and we wish to test whether including the oil price reduces the contribution of our 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' aquisition 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 (Hamilton (2009), Kilian (2009)) have shown that most of the oil price movements in 2007-2008 and over a longer sample period are due to global demand shocks. 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 GDP deflator inflation have captured oil price shocks in our baseline TV-VAR model.

7 Conclusions

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). 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 a latent factor summarizing a very large number of financial variables.

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 constraint. 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.

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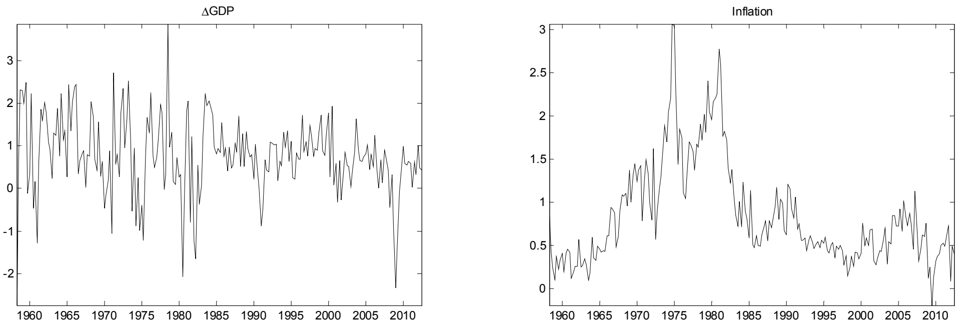
Table 1: Overview on the empirical literature on time-varying macro-financial linkages

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.

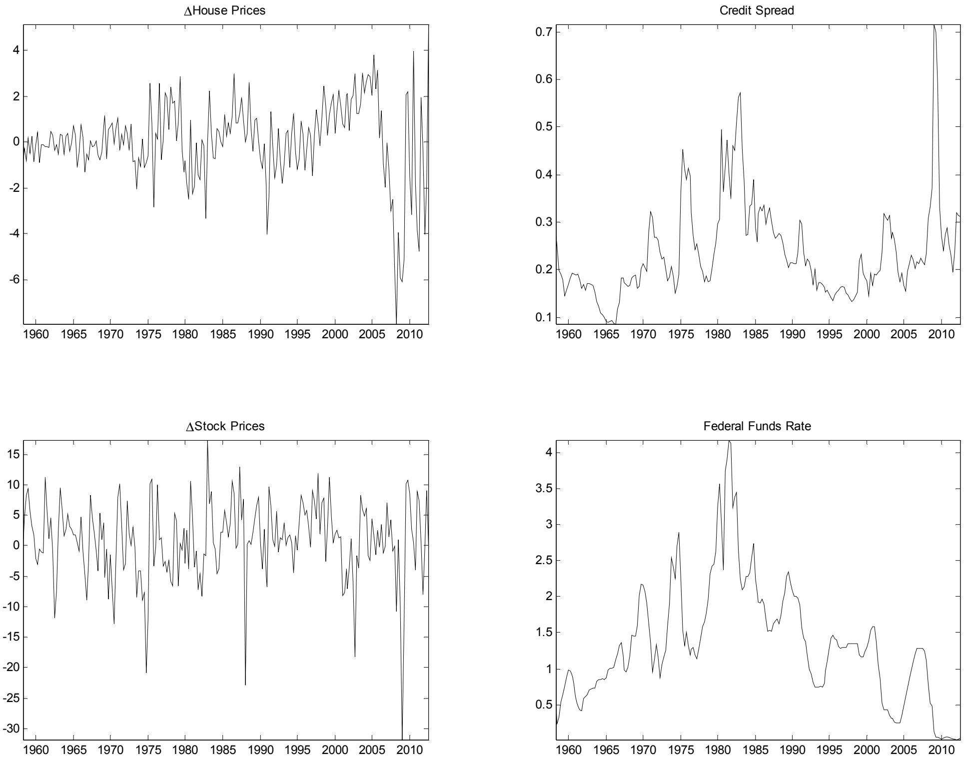
Notes: In the VAR applications, which look at shocks to a financial conditions or a financial stress index, the index is counted as one variable. The indexes are, however, typically formed of a large number of financial variables.

Figure 1: Time series plots

(a) Macroeconomic series



(b) Observable financial series



(c) NFCI from the Federal Reserve Bank of Chicago

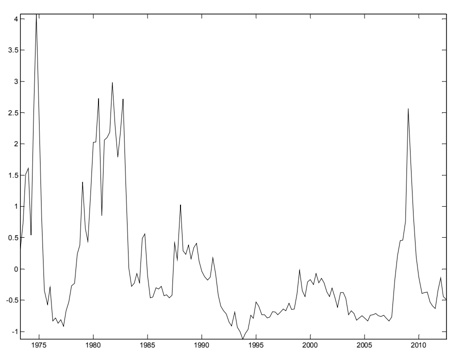
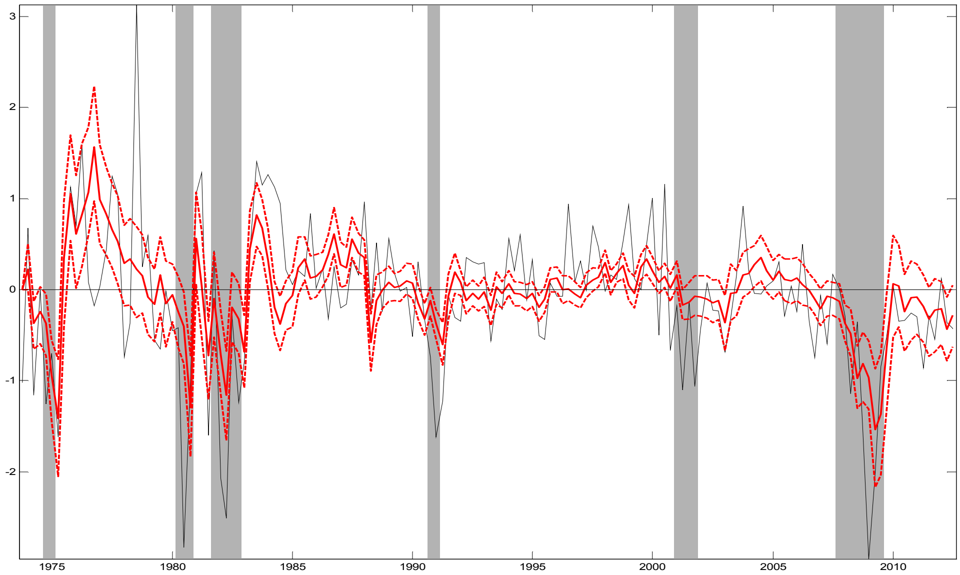
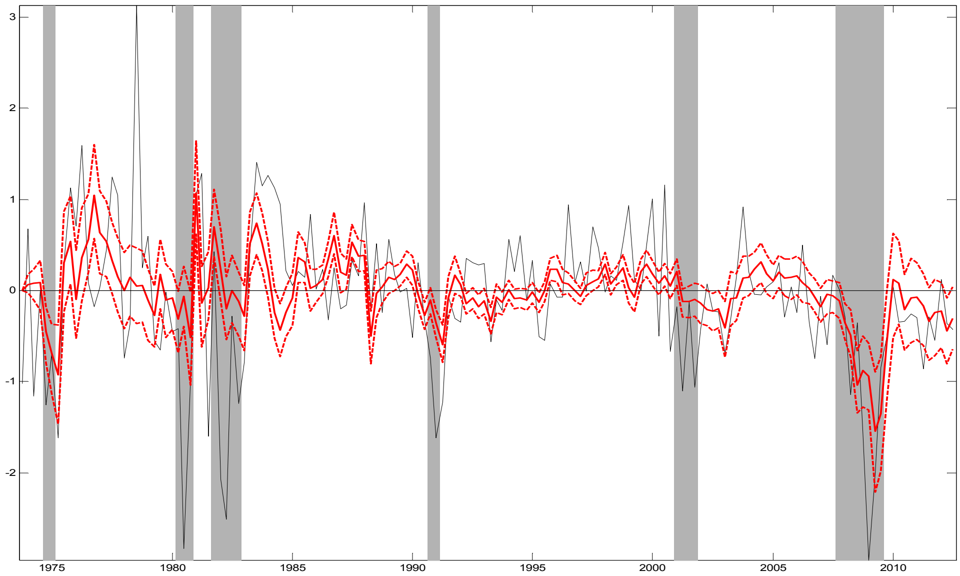


Figure 2: Overall contribution of financial shocks estimated from the TV-VAR (median and 1 standard deviation percentiles)

(a) Including shocks to the Federal Funds rate



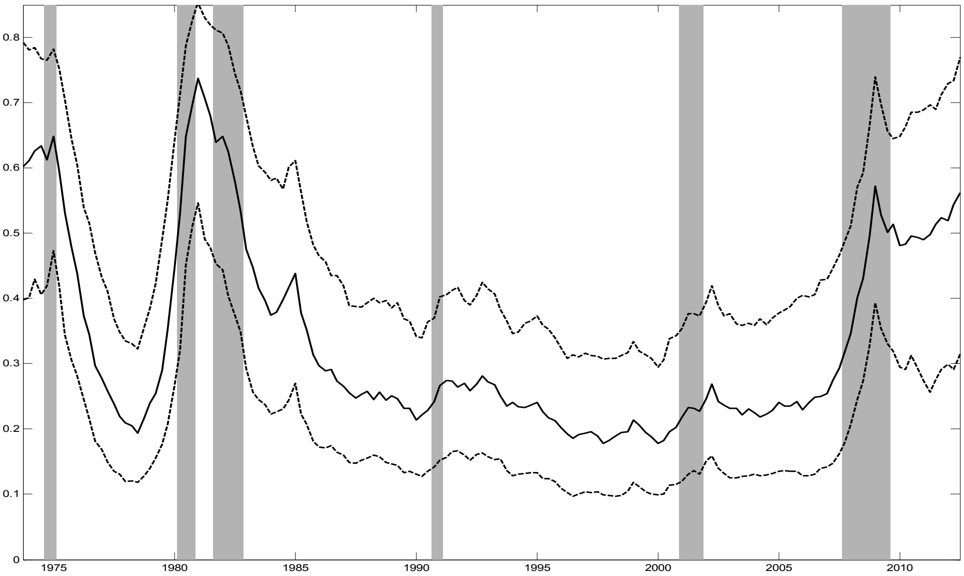
(b) Excluding shocks to the Federal Funds rate



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 3: 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

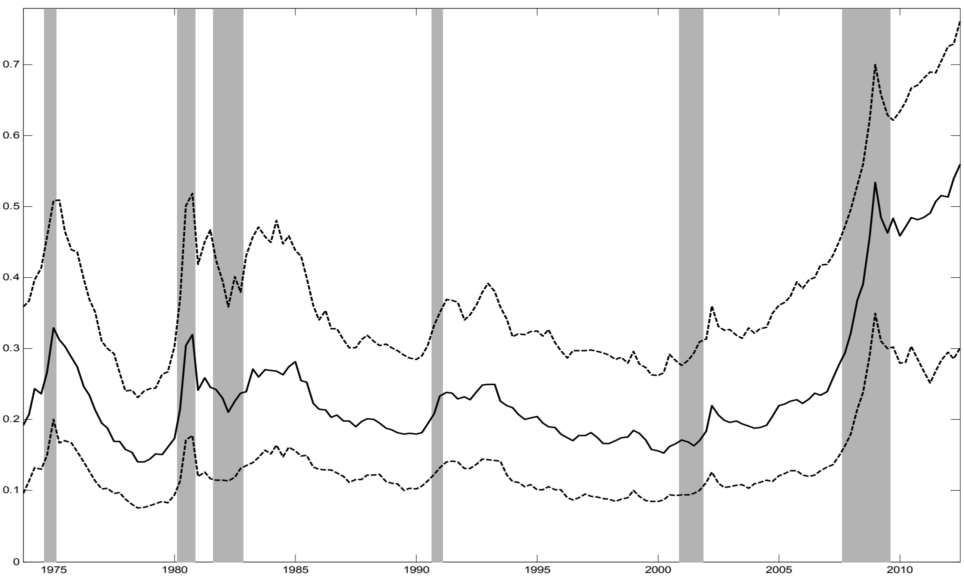
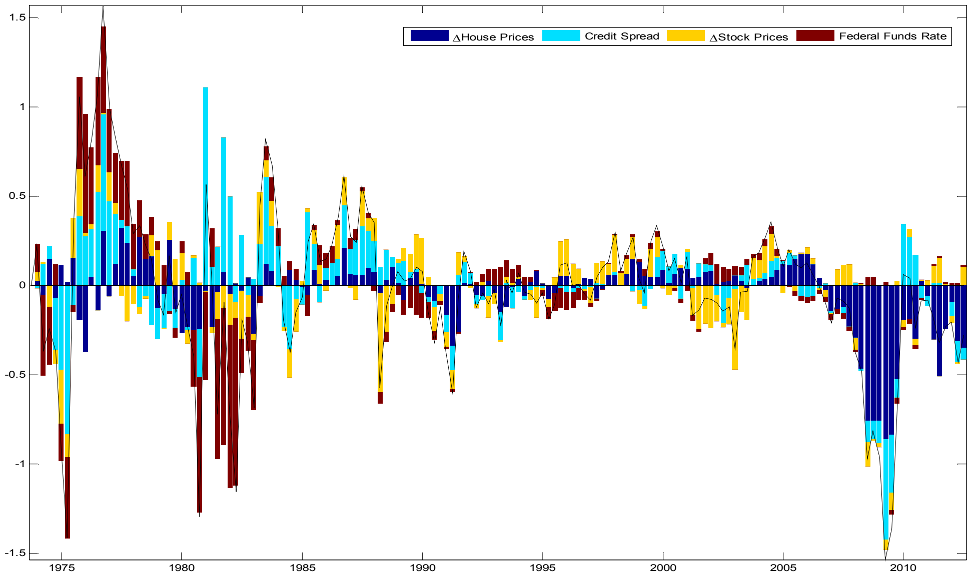


Figure 4: Contributions of individual financial shocks estimated from the TV-VAR (median estimates)



Notes: see notes to Figure 2.

Figure 5: 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)

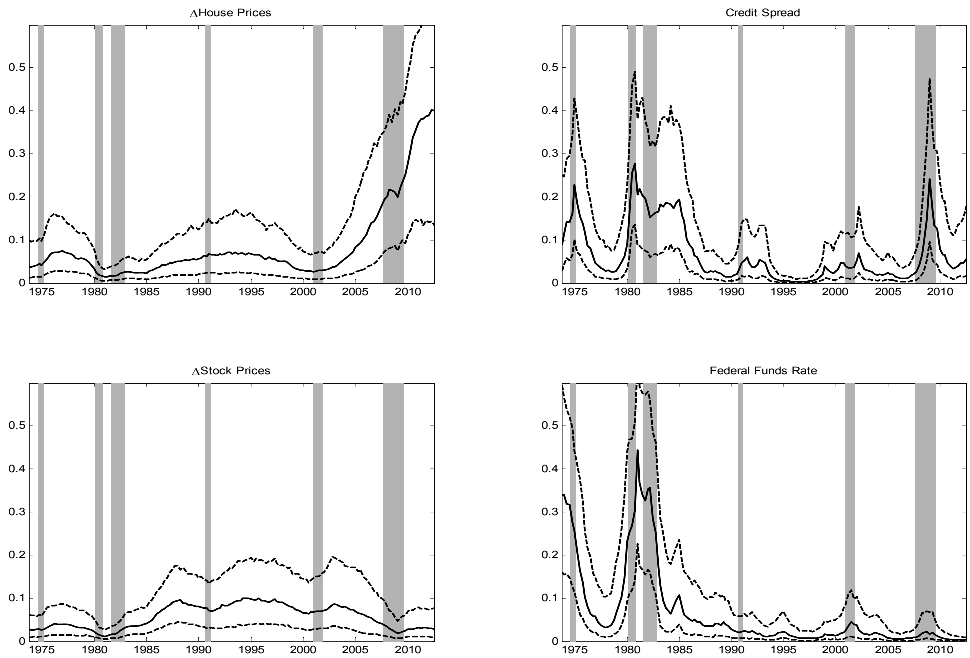


Figure 6: Standard deviations of structural shocks estimated from the TV-VAR (median estimates and 1 standard deviation percentiles)

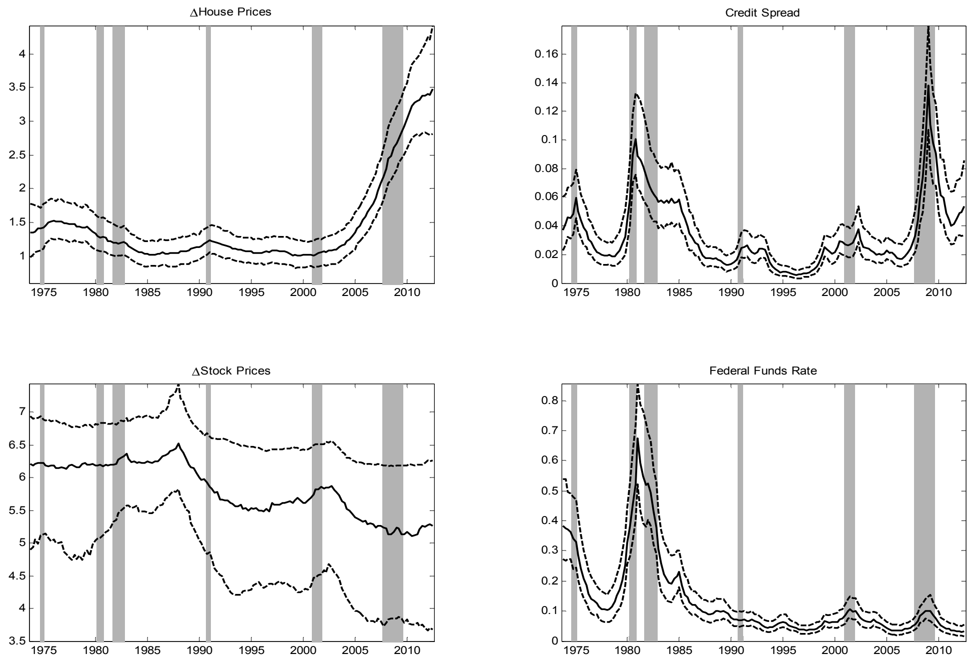


Figure 7: Impulse responses of GDP growth to unit financial shocks estimated from the TV-VAR (median estimates)

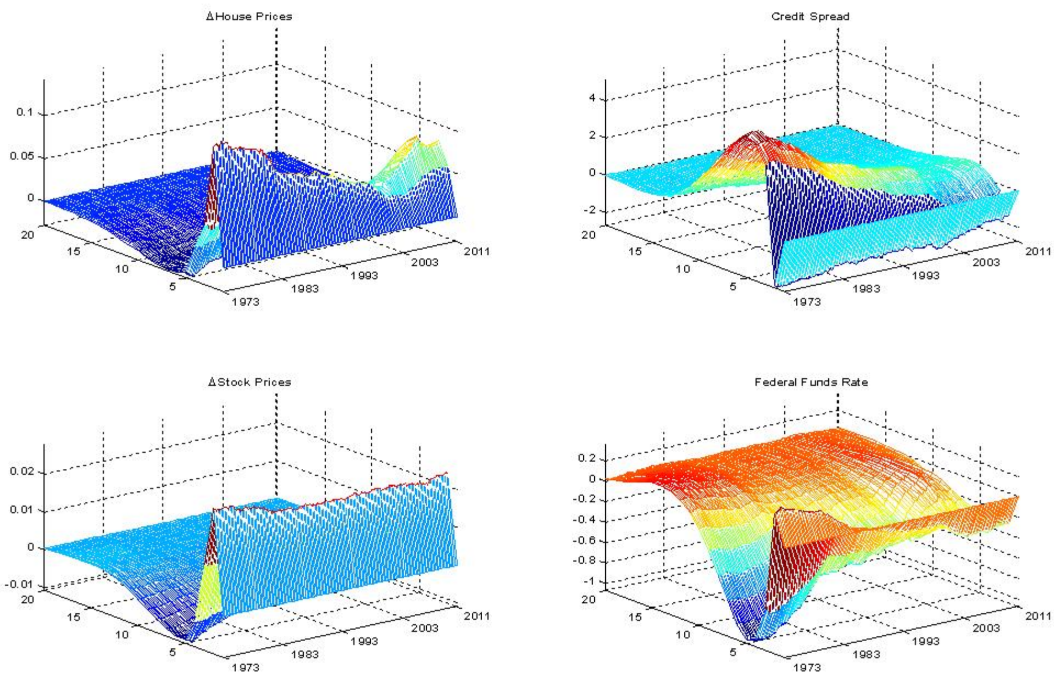
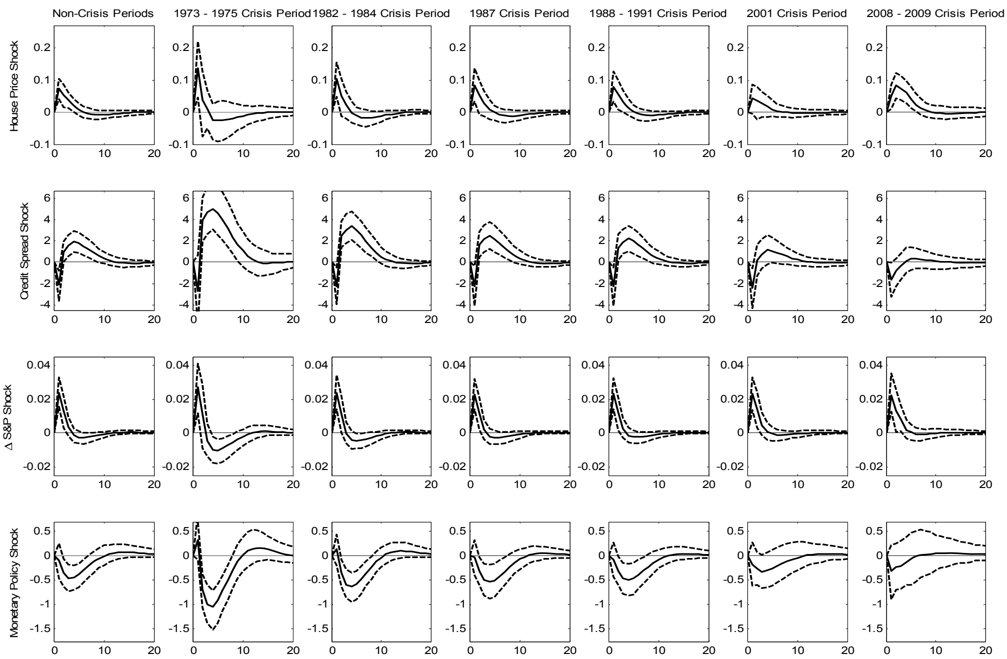


Figure 8: Impulse responses of GDP growth to unit financial shocks estimated from the TV-VAR on average over selected periods (median estimates and 1 standard deviation percentiles)

(a) Financial crisis vs. non-crisis periods



(b) Non-crisis periods

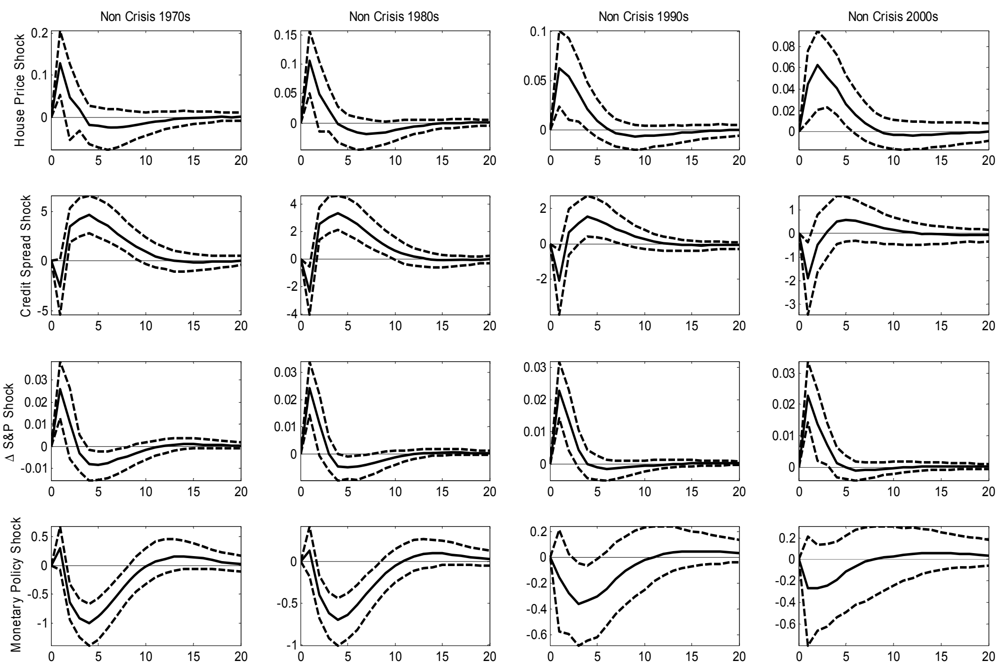
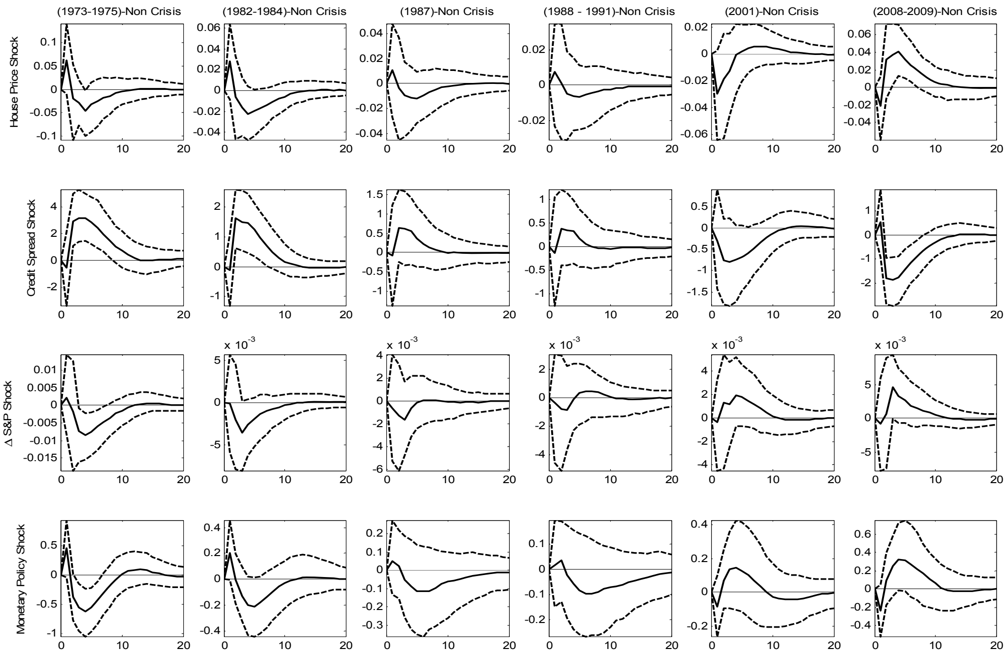


Figure 9: Differences of impulse responses of GDP growth to unit financial shocks estimated from the TV-VAR on average over selected periods (median estimates and 1 standard deviation percentiles)

(a) Financial crisis vs. non-crisis periods



(b) Non-crisis periods

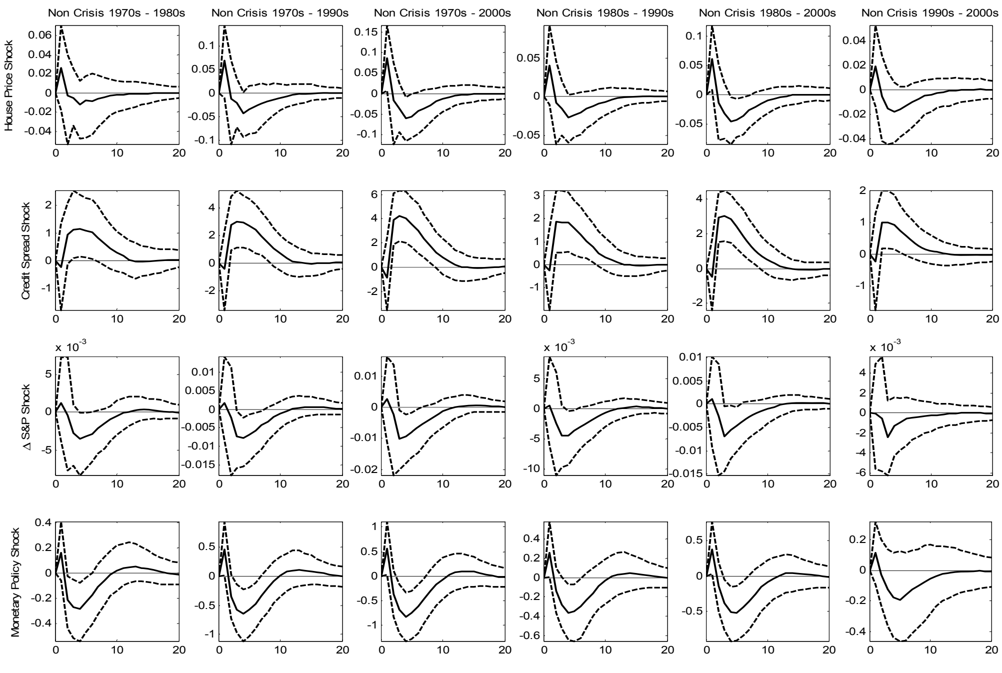
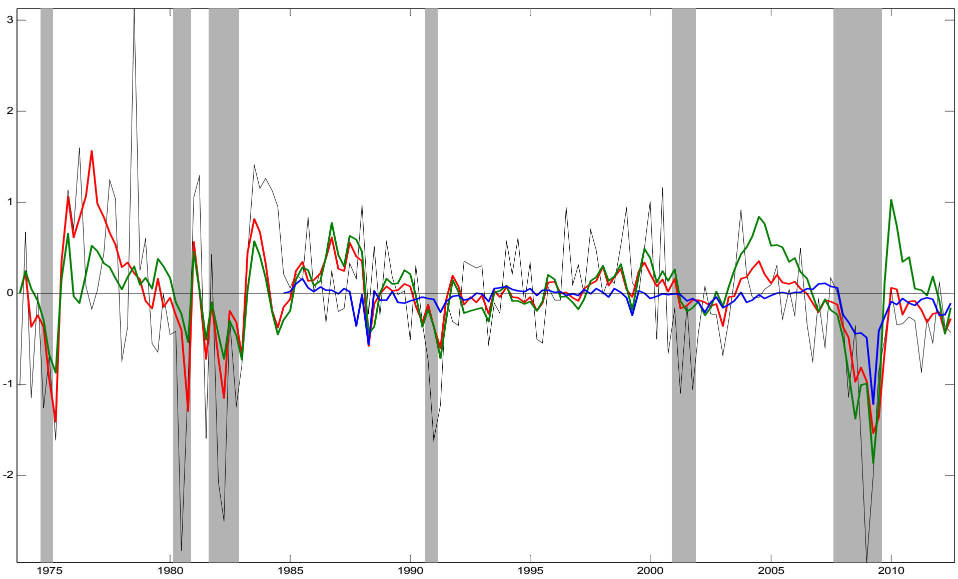
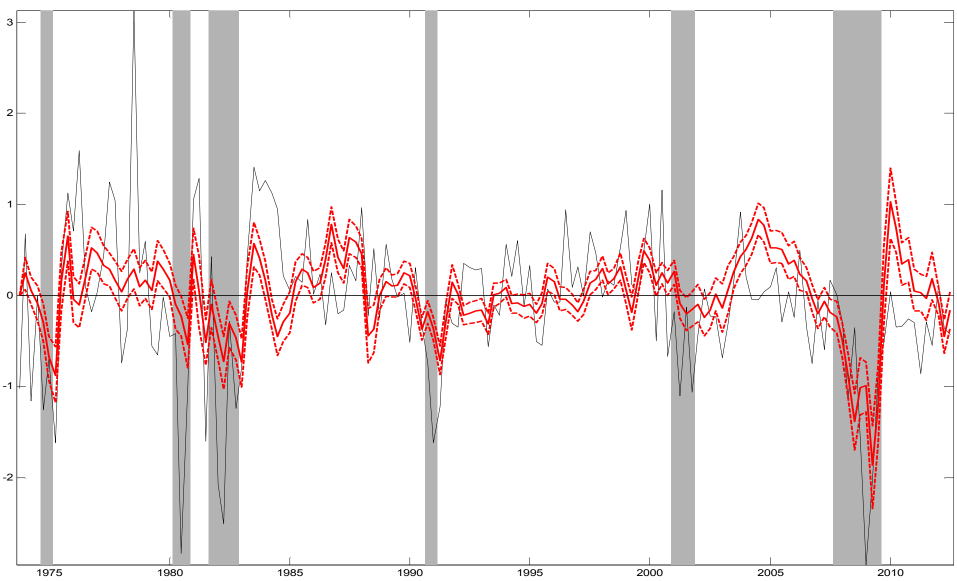


Figure 10: Overall contribution of financial shocks

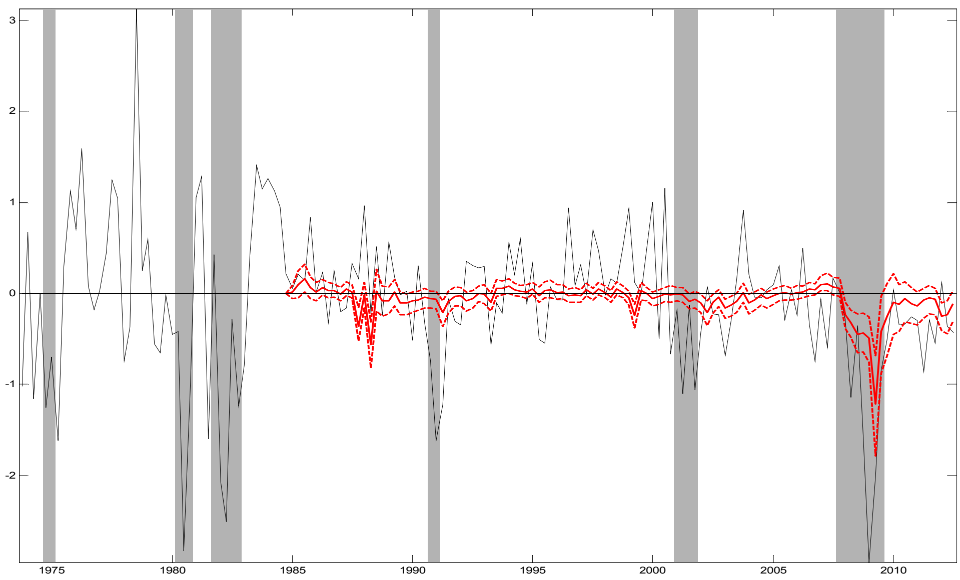
(a) Median estimates



(b) C-VAR



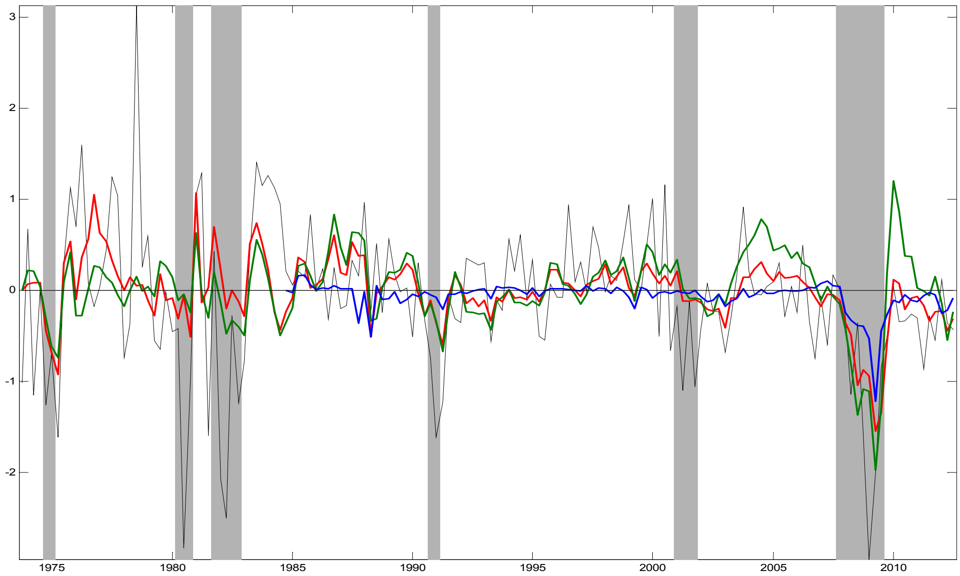
(c) TV-VAR with FCI



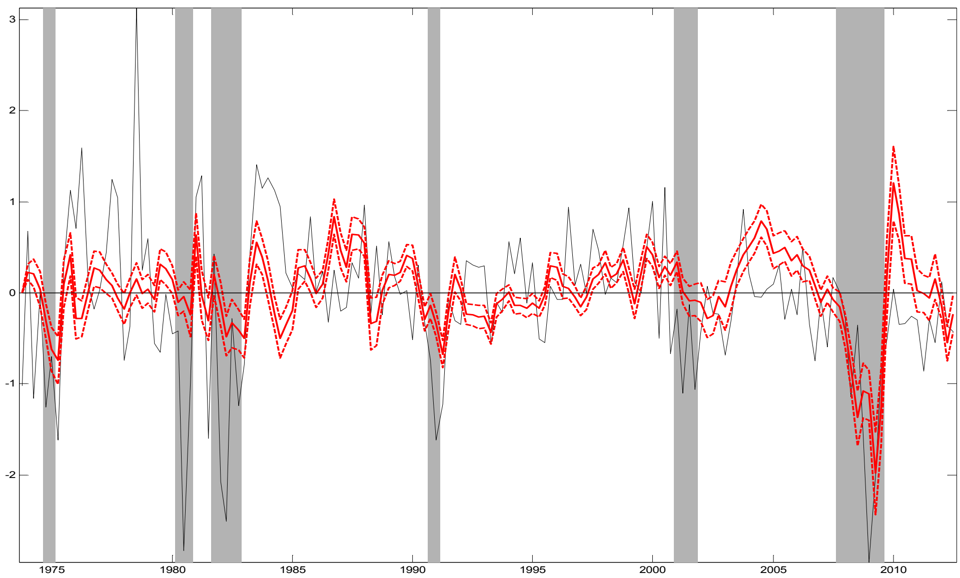
Notes: Black: all shocks, Panel (a): red: derived from TV-VAR; green: C-VAR; blue: TV-FCI-VAR (starting in 1984Q3), Panels (b) and (c): solid red: median; dashed red: 16th and 84th percentiles. See also notes to Figure 2 for more information.

Figure 11: Overall contribution of financial shocks excluding shocks to the Federal Funds rate

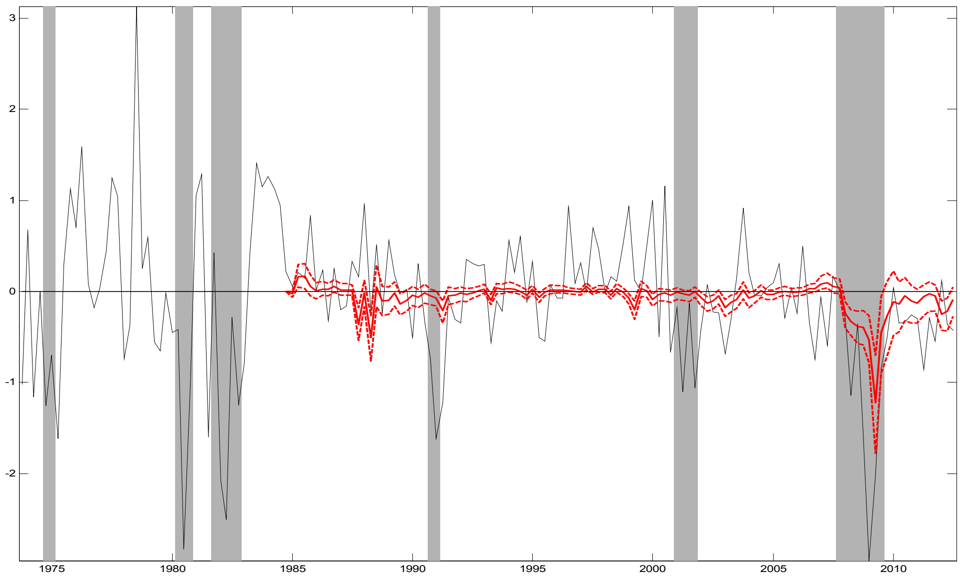
(a) Median estimates



(b) C-VAR



(c) TV-VAR with FCI

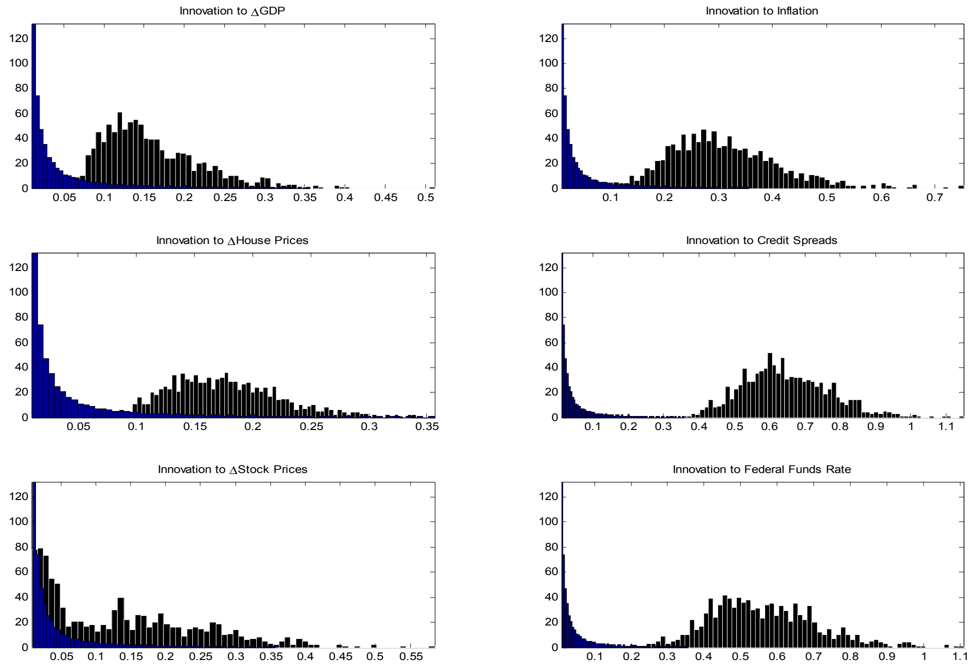


Notes: Black: all shocks, Panel (a): red: derived from TV-VAR; green: C-VAR; blue: TV-FCI-VAR (starting in 1984Q3), Panels (b) and (c): solid red: median; dashed red: 16th and 84th percentiles. See also notes to Figure 2 for more information.

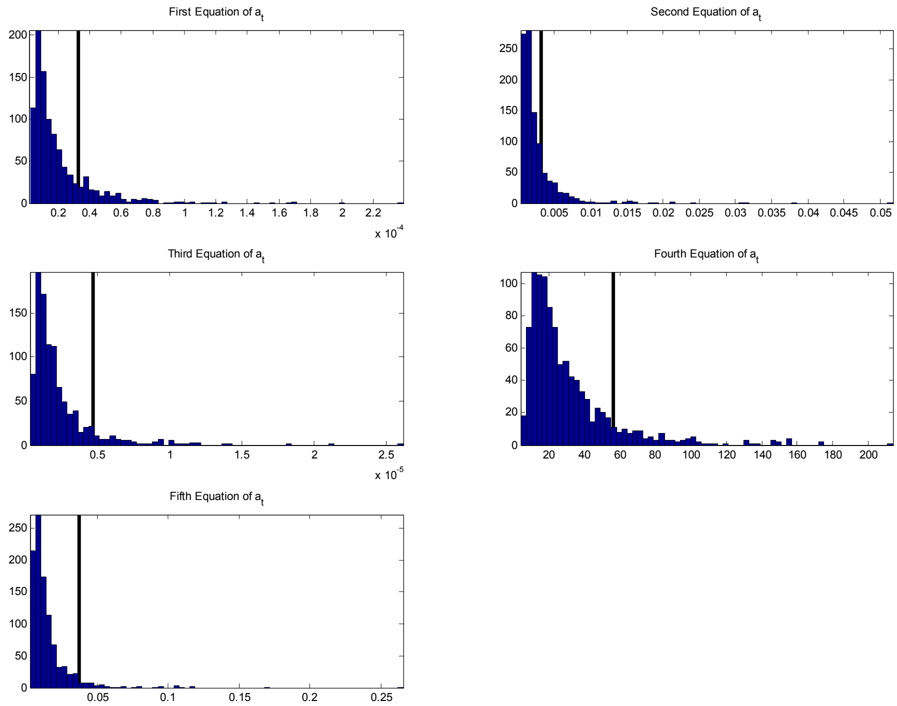
Appendix

Figure A.1: Prior (blue) and posterior (black) distributions

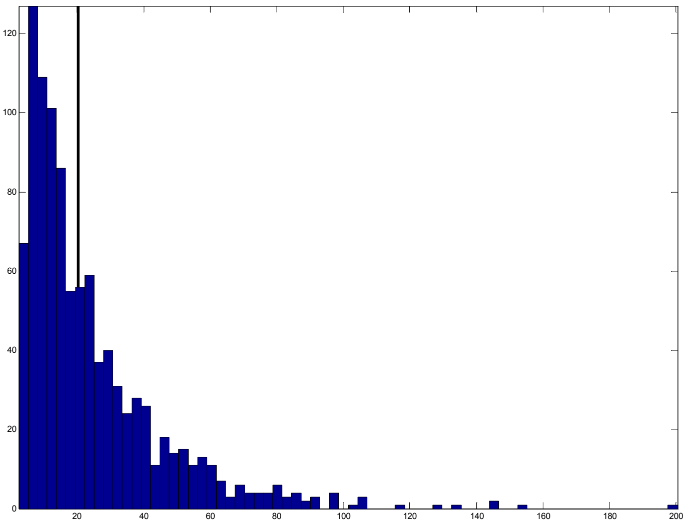
(a) Elements of Z



(b) Elements of S



(c) Histogram of Q



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

Figure A.2: Results of test for convergence of the hyperparameters and the states

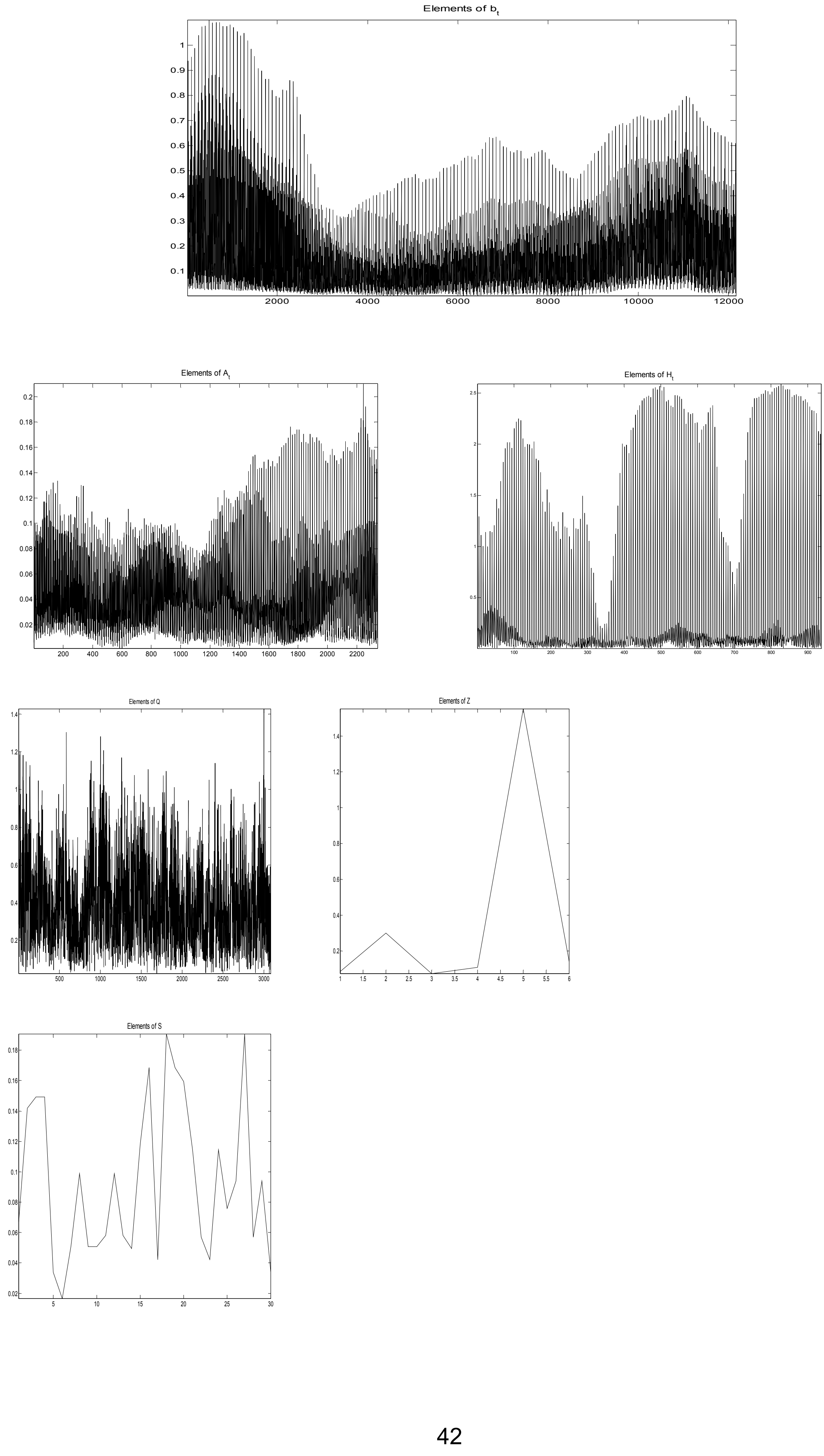
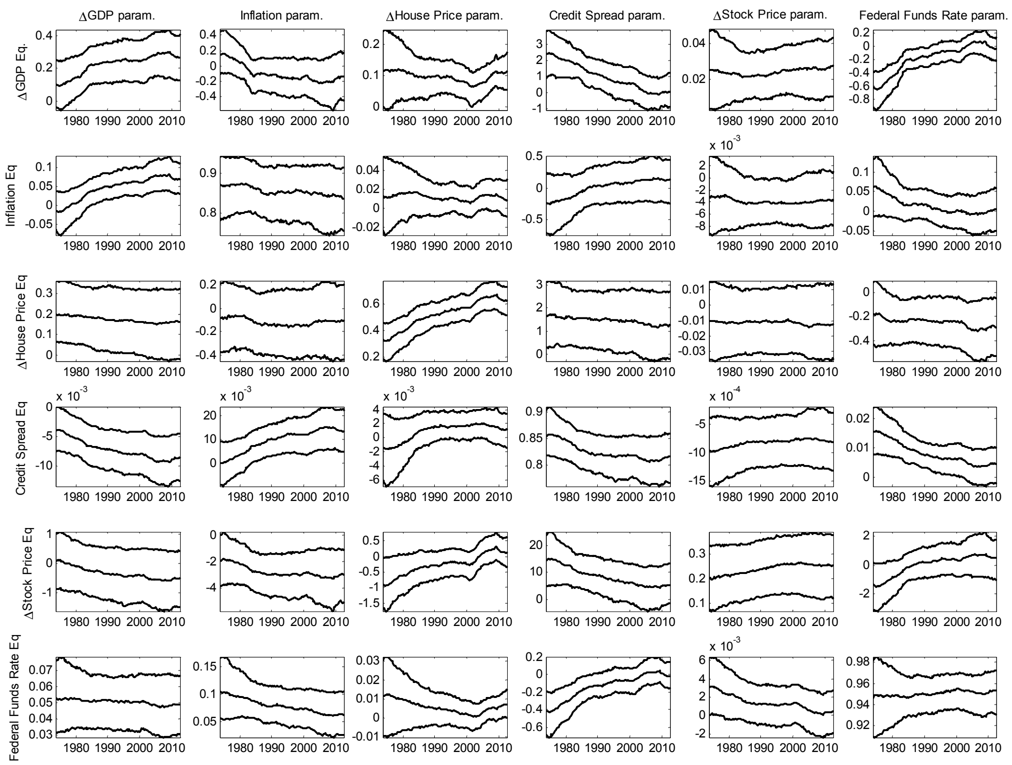


Figure A.3: Parameter evolution

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



(b) Contemporaneous relations (elements of A_t)

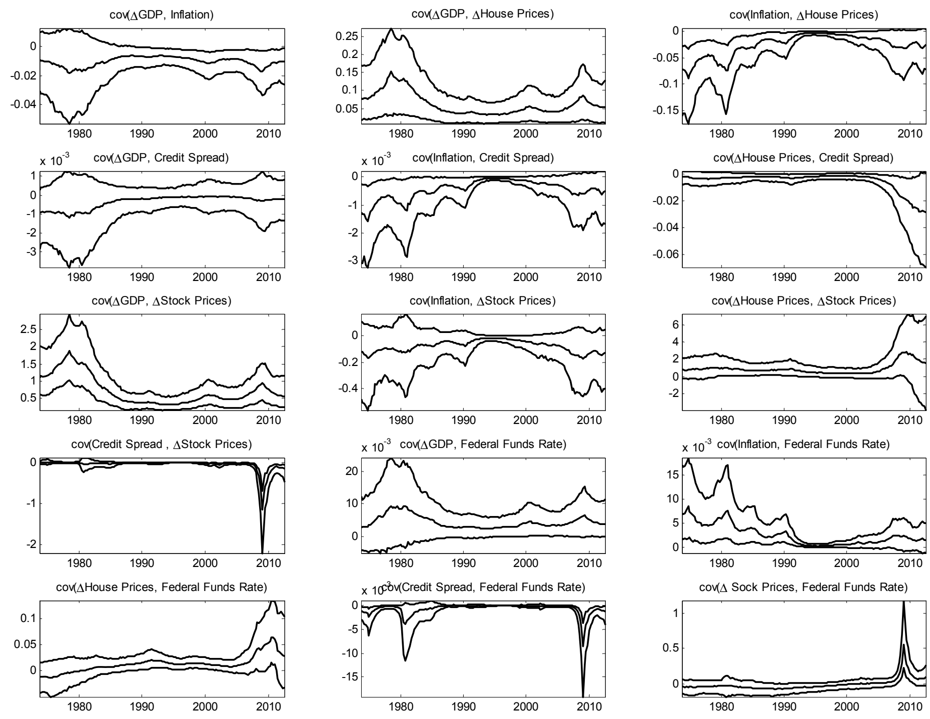


Figure A.4: Impulse responses of GDP growth to unit financial shocks estimated from the C-VAR (median estimates and 1 standard deviation percentiles) and from the TV-VAR on average over the entire period (median estimates)

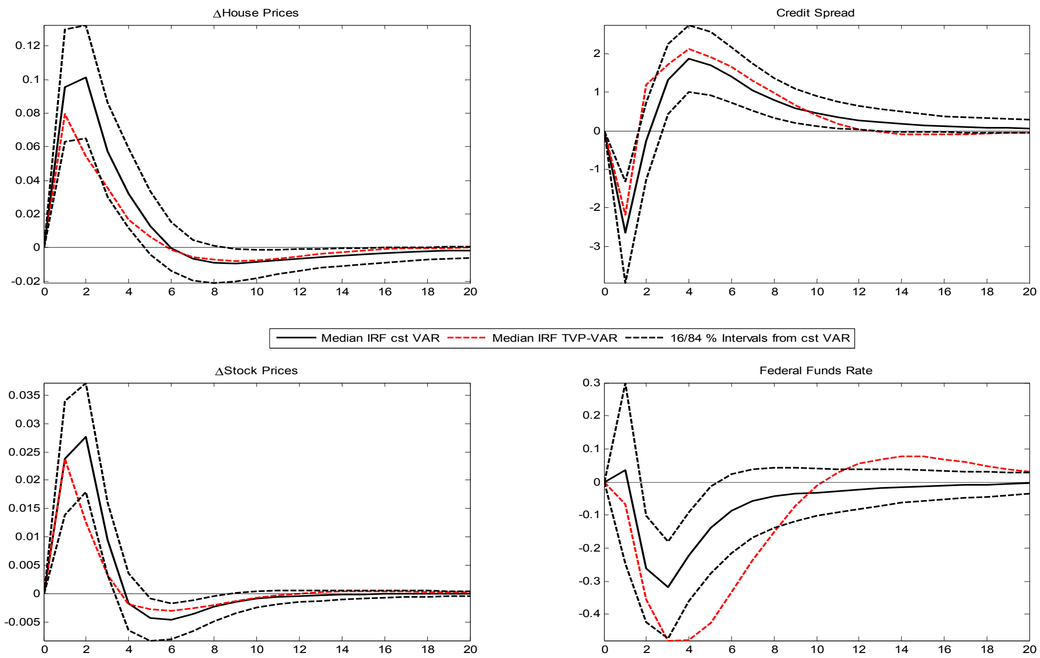
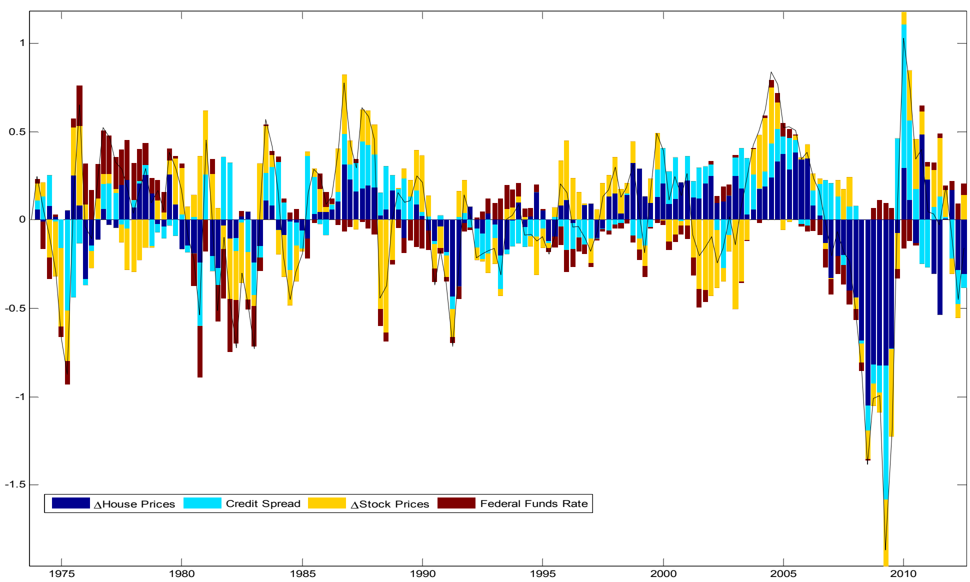
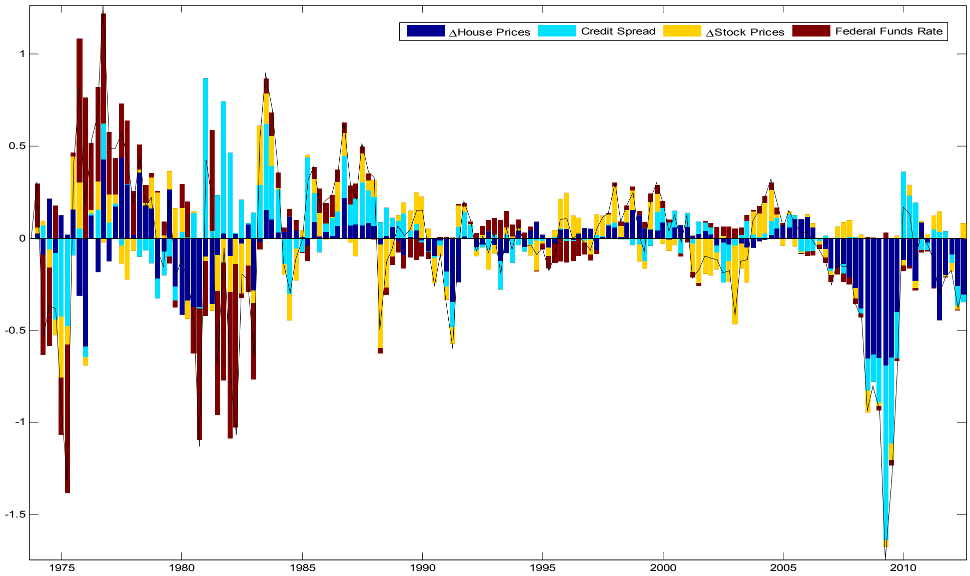


Figure A.5: Contributions of individual financial shocks from the C-VAR (median estimates)



Notes: see notes to Figure 2.

Figure A.6: 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 2.

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 → Federal Funds rate → credit spread → stock price inflation (median estimates and 1 standard deviation percentiles)

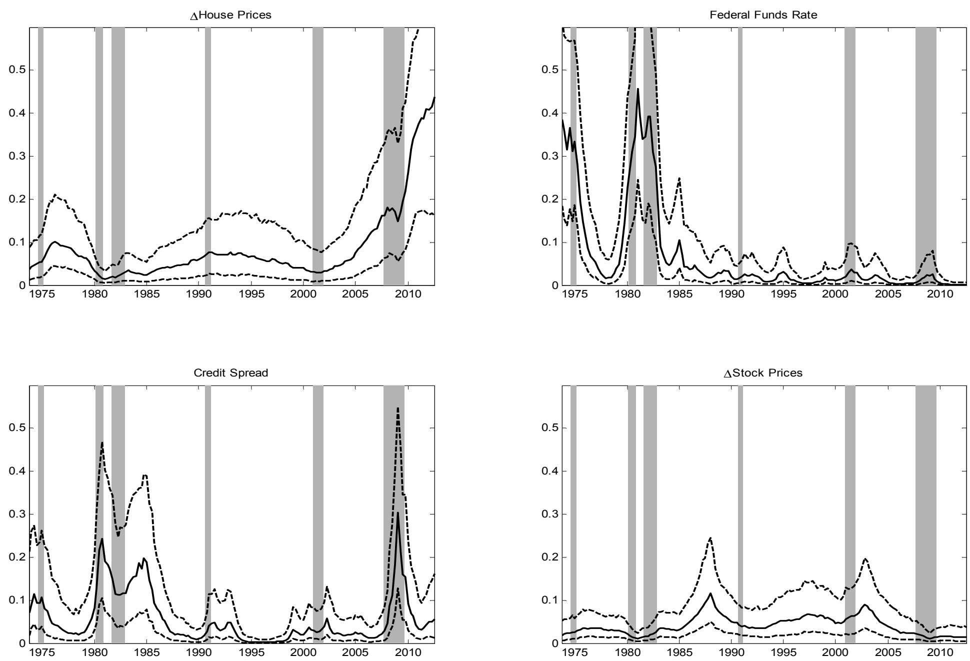


Figure A.8: Standard deviations of structural shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation → Federal Funds rate → credit spread → stock price inflation (median estimates and 1 standard deviation percentiles)

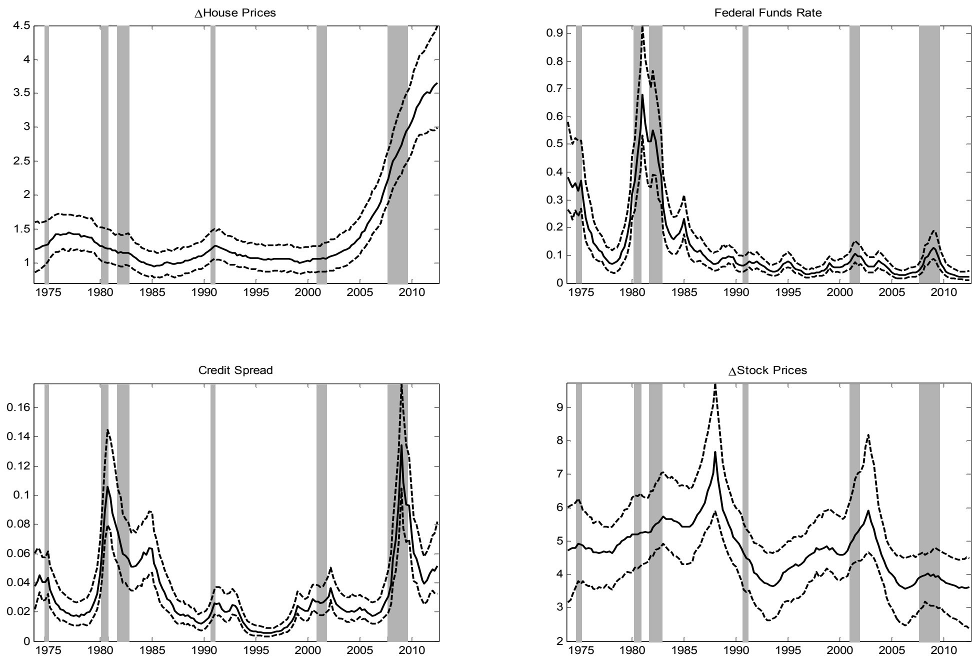


Figure A.9: Impulse responses of GDP growth to unit financial shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation → Federal Funds rate → credit spread → stock price inflation (median estimates)

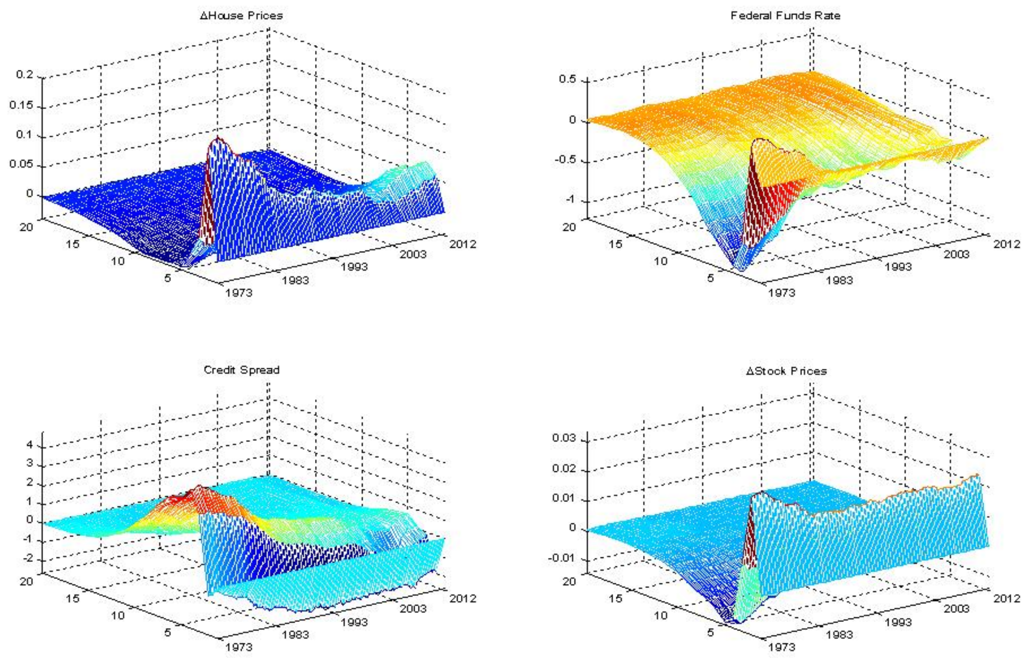
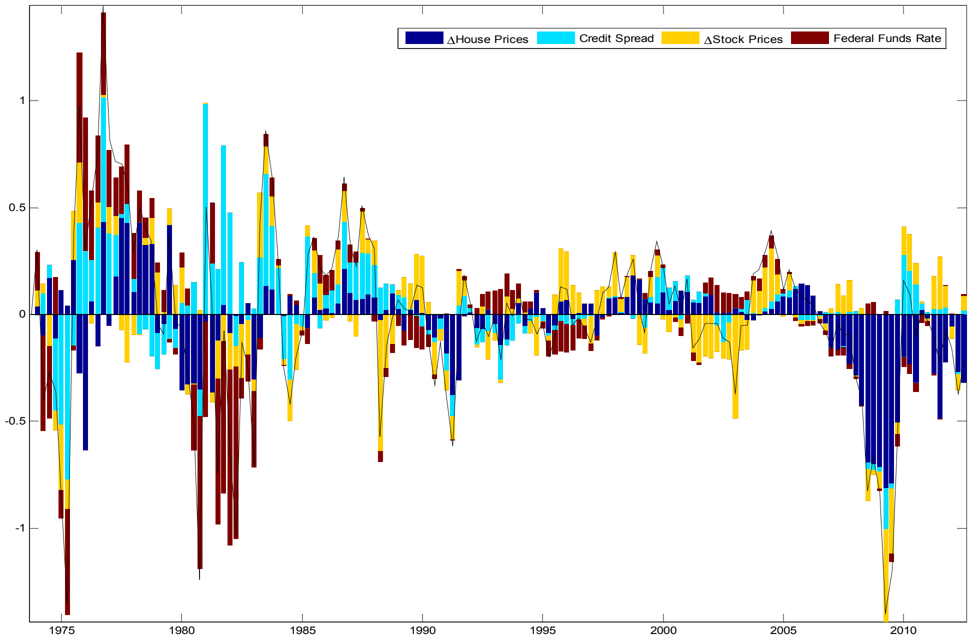


Figure A.10: Contributions of individual financial shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation → stock price inflation → credit spread → Federal Funds rate



Notes: see notes to Figure 2.

Figure A.11: 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)

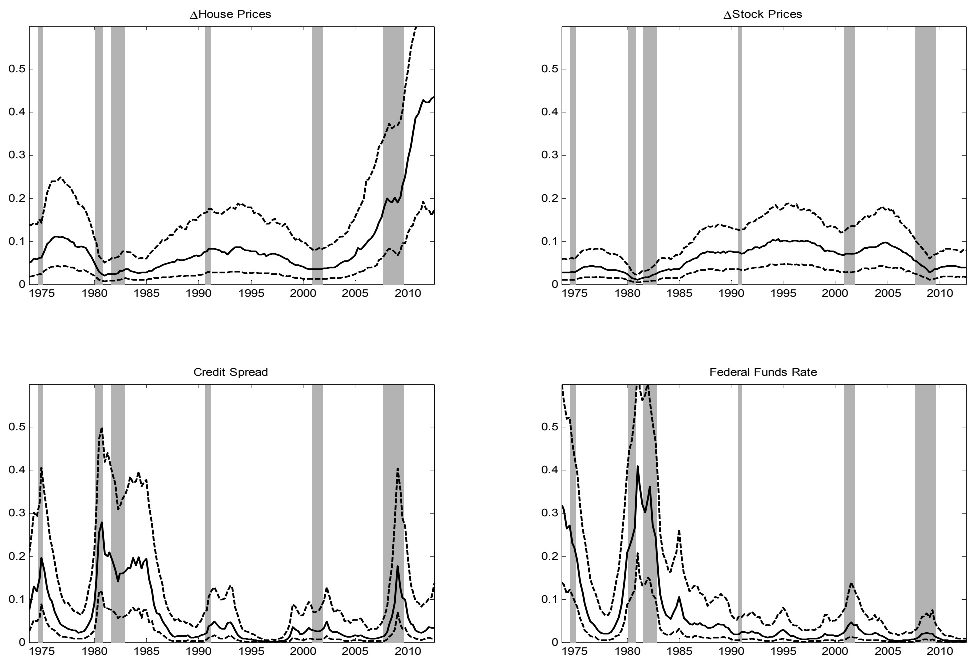


Figure A.12: Standard deviations of structural shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation → stock price inflation → credit spread → Federal Funds rate (median estimates and 1 standard deviation percentiles)

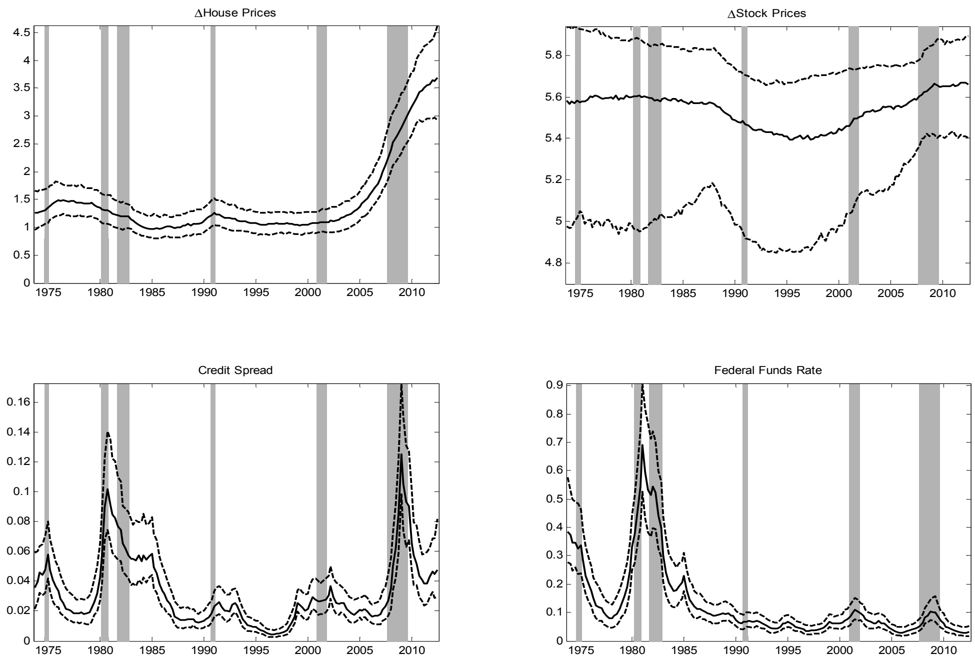


Figure A.13: Impulse responses of GDP growth to unit financial shocks estimated from the TV-VAR where the ordering in the financial block is: house price inflation → stock price inflation → credit spread → Federal Funds rate (median estimates)