Online Appendix to

Time Variation in Macro-Financial Linkages*

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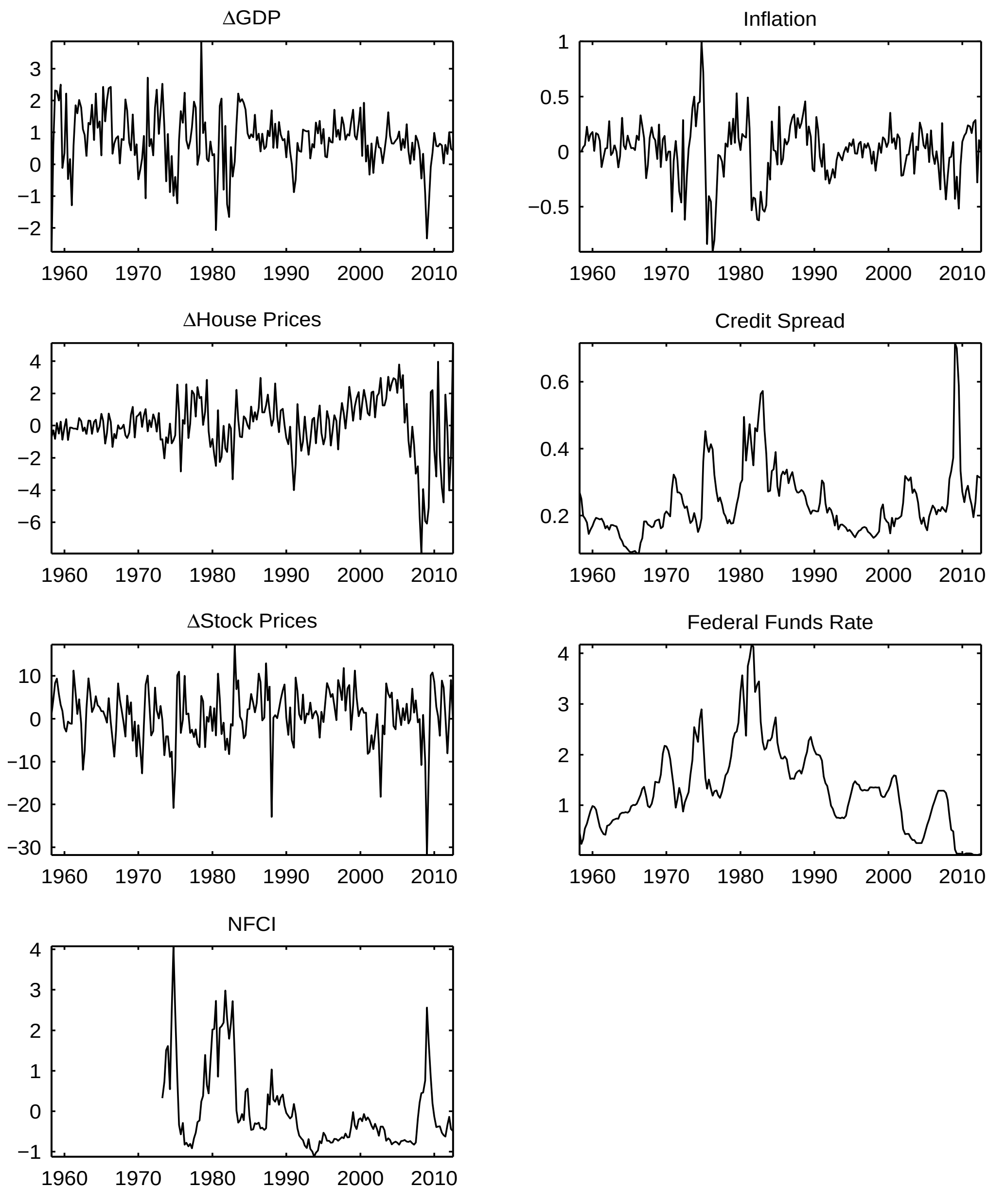
Contents

*The views expressed in this paper do not necessarily reflect the views of the Deutsche Bundesbank.

1 Time-series data

In Figure 1 we plot the data used in the empirical application.

Figure 1: **Time series plots**



2 Priors

The specification of the prior distribution and hyperparameters closely follows the specifications used in Primiceri (2005) and Cogley and Sargent (2005) . The first 15 years (sixty observations, from 1958:I to 1972:IV) are used to calibrate the prior distributions. For example, the mean and the variance of b_0 are chosen to be the OLS point estimates (b_{OLS}) and four times its variance in a time invariant VAR, estimated on the small initial subsample. In the same way, the prior for A_0 is obtained. For $\ln h_{0i}$ instead, the mean of the distribution is chosen to be the logarithm of the OLS point estimate of the standard errors of the $i-th$ equation in the time invariant VAR, while the variance is set to 10. Note that 10 is huge on a log scale. The prior distribution of each of the diagonal elements in Z is inverse gamma with a single degree of freedom and a scale parameter of 0.1. Finally, degrees of freedom and scale matrices are needed for the inverse-Wishart prior distributions of the hyperparameters. The degrees of freedom are set to $2\ldots6$ for the six blocks of S (basically, 1 plus the dimension of each matrix). For Q the degrees of freedom are set to 1 plus the dimension of b_t. The scale matrices, Q, $S_1 \ldots S_6$, are chosen to be constant fractions of the variances of the corresponding OLS estimates on the initial subsample. Summarizing, the priors take the form:

$$
\begin{aligned}
b_0 &\sim N(b_{OLS}, 4 \cdot V(b_{OLS})) \\
A_0 &\sim N(A_{OLS}, 4 \cdot V(A_{OLS})) \\
\ln h_0 &\sim N(\ln h_{OLS}, 10) \\
Q &\sim IW(k_Q^2 \cdot (dim(b_t)+1) \cdot V(b_{OLS}), (dim(b_t)+1)) \\
Z_{i,i} &\sim IG\left(\frac{v}{2}, \frac{1}{2}\right) \text{ for } i = 1 \ldots M \\
S_i &\sim IW(k_S^2 \cdot (i+1) \cdot V(A_{i,OLS}), i+1) \text{ for } i = 1 \ldots M-1
\end{aligned}
$$

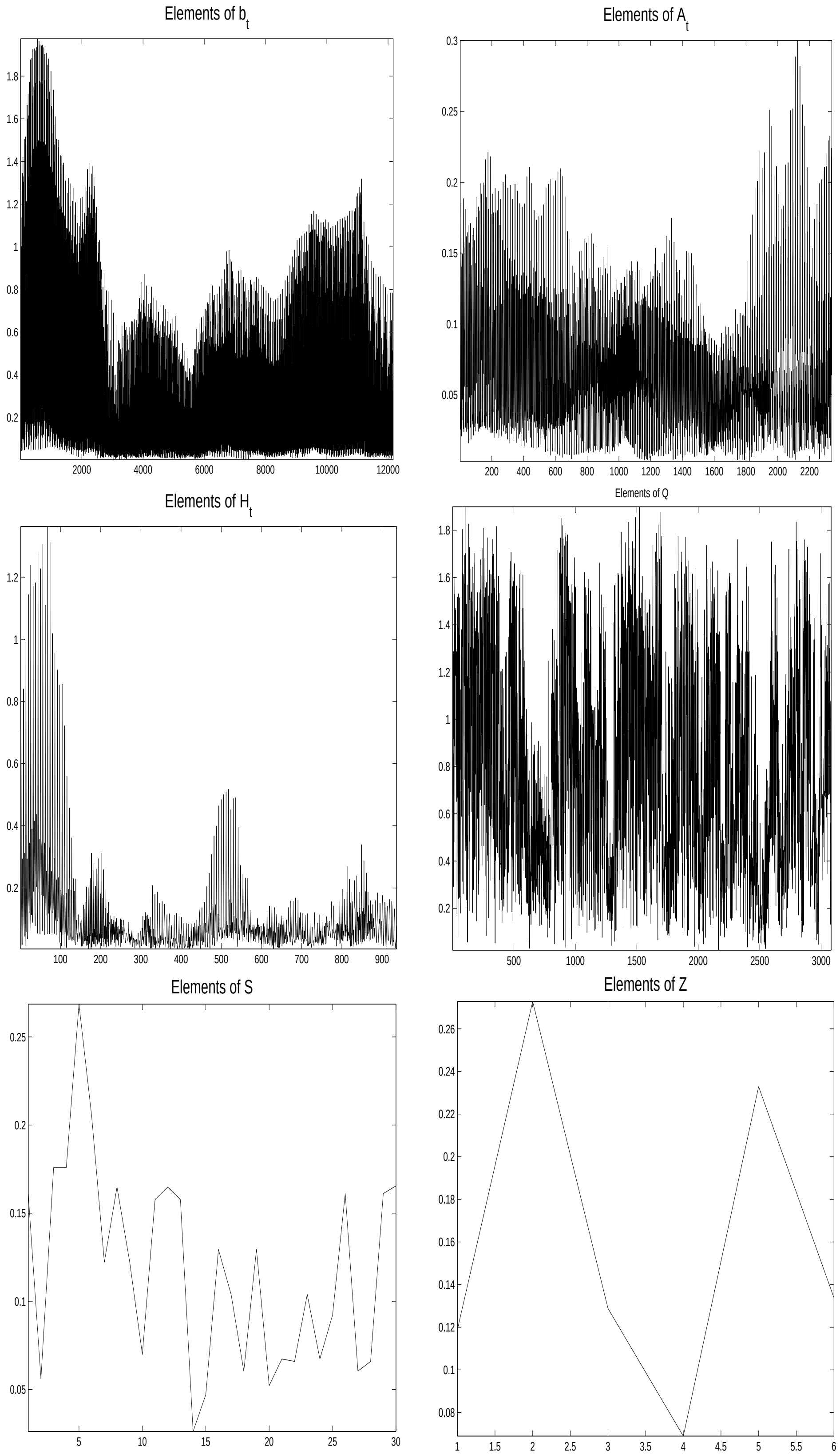
where S_i denotes the $i-th$ blocks of S, while $A_{i,OLS}$ stands for the correspondent blocks of A_{OLS}. The benchmark results presented in this section are obtained using the following values: $k_Q = 0.01$, $k_S = 0.1$, $v = 0.1$. Set in this way, the priors are not flat, but diffuse and uninformative.

The MCMC algorithm simulates the joint posterior distribution by sequentially drawing from the conditional distributions which all have a familiar form (see Cogley and Sargent (2005) and Primiceri (2005)). We use a burn-in period of 50,000 iterations to ensure convergence to the ergodic distribution. We then draw 10,000 times from the target distribution keeping every 10th draw to reduce the autocorrelation across draws.

3 Convergence Tests

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

Figure 2: **Convergence statistics**



4 Parameter Evolution

In order to gauge the underlying sources of the time variation in the impulse responses we show in Figure 3 the evolution of the autoregressive parameters (i.e. the elements of B_t summed over the two lags) and in Figure 4 the evolution of the contemporaneous relations between the variables (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.

Figure 3: **Autoregressive parameters summed over lags (elements of B_t)**

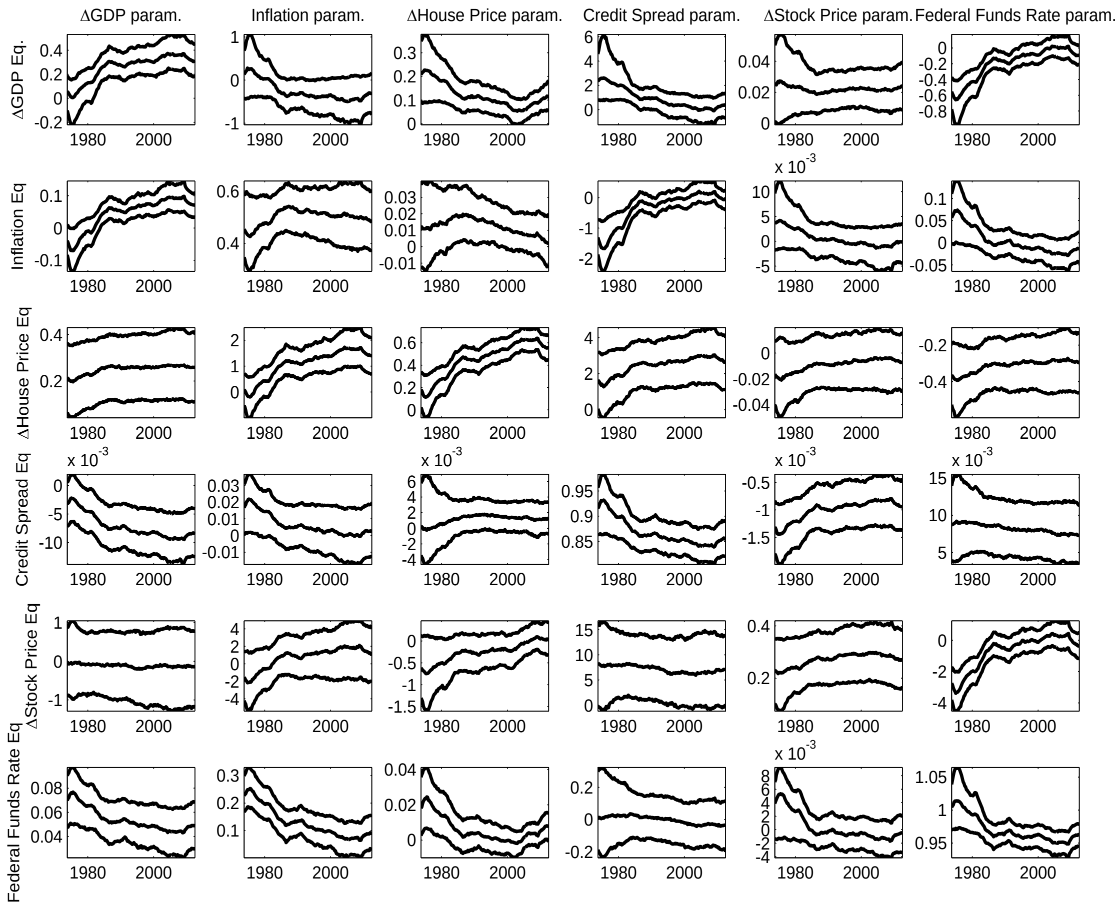
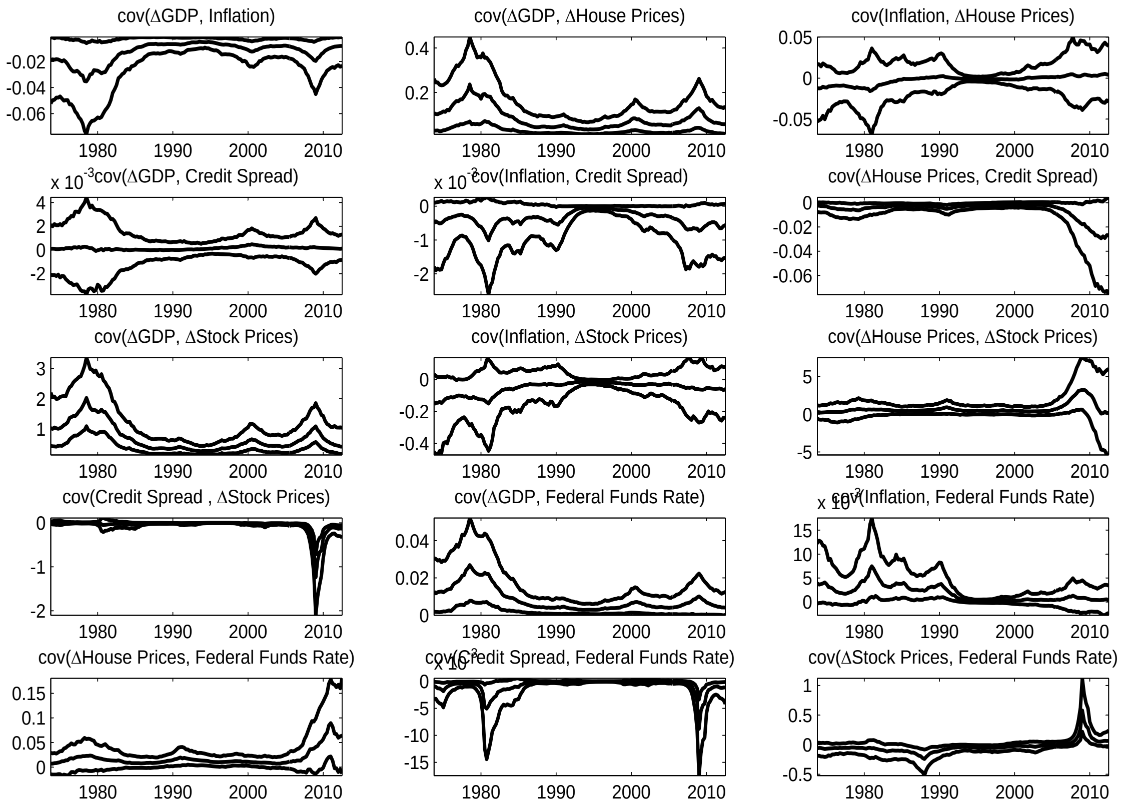


Figure 4: **Contemporaneous relations (elements of A_t)**



5 Prior-posterior comparison

We compare in Figures 5-7 the posterior distribution of the hyperparameters Z_i, S_i and Q with the corresponding distributions implied by the prior. These parameters are crucial as they control the degree of time variation in the state parameters. For the matrix Q (S_i) we plot the density estimates of the distributions of the posterior and prior trace statistics. 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.

Figure 5: **Prior vs. posterior of Z_i**

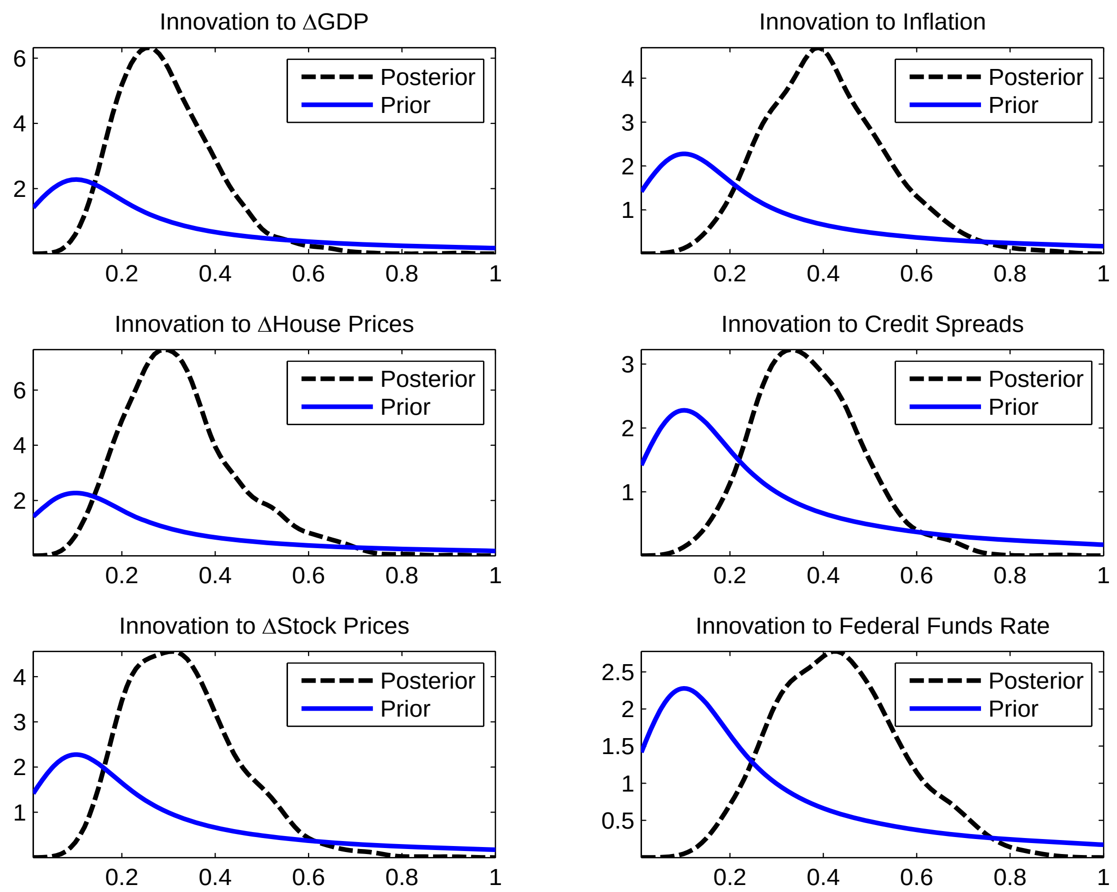


Figure 6: **Prior vs. posterior of** S_i

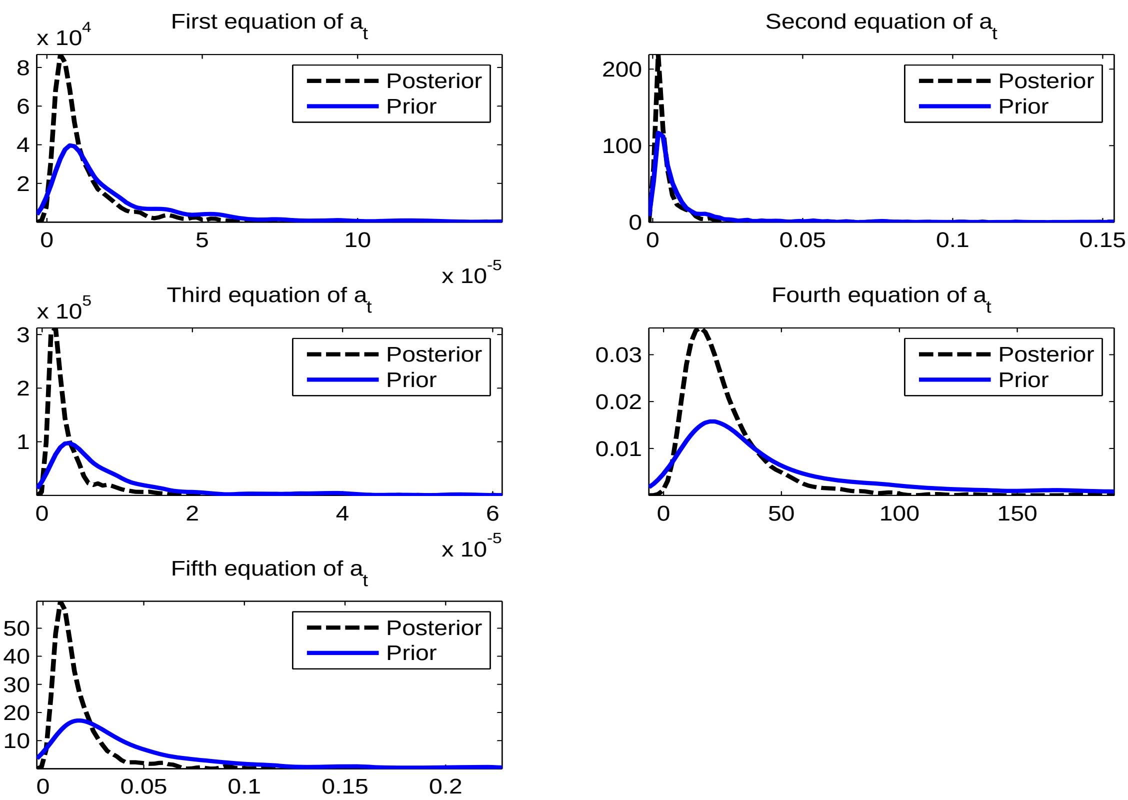
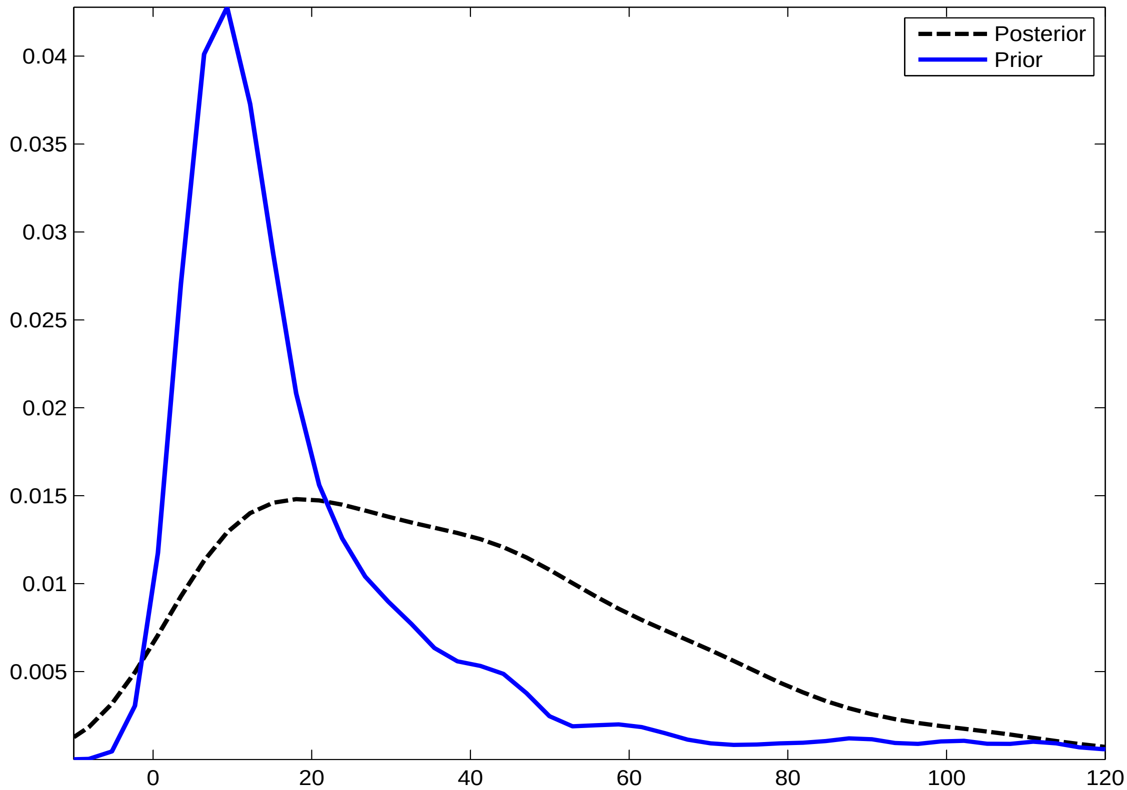


Figure 7: **Prior vs. posterior of** Q



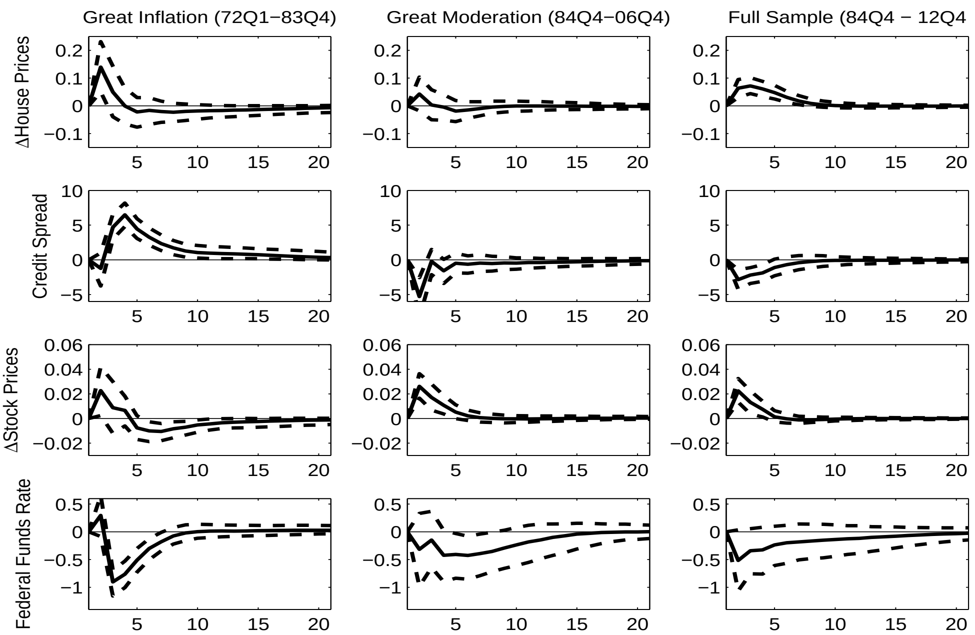
6 Constant parameter VAR over subsamples

To obtain a first idea on the sources of time variation, we estimate constant parameter VAR models for three sub-samples: 1972Q4-1983Q4, 1984Q1-2006Q4 and 1984Q1-end of our sample.[1] 1984Q1 marks the start of the Great Moderation and represents a natural break point. The second period ends before the Global Financial Crisis, whereas the third period includes the crisis (we prefer not to fit a model to the crisis sample period only, which is very short). Figure 8 shows impulse responses from the three VAR models to financial shocks, normalized to raise house price inflation, the credit spread, stock price inflation and the Federal Fund rate by 1 percent or 1 percentage point. There is substantial time variation in the effects over time. House price shocks have more persistent effects on GDP growth in the last sample compared to the Great Moderation sample. The overshooting of GDP growth (from negative to positive) after the credit spread shock has become smaller over time. Finally, the effects of monetary policy shocks have become weaker, in line with much of the previous empirical literature (see Table A.2 in Eickmeier et al. (2015)). In addition, the size of the shocks, measured as the impact effect of one standard deviation shocks on the financial variables, has changed over time. The size of Federal Funds rate shocks has become significantly smaller since the 1970s; house price shocks are larger in the sample including the Great Recession compared to the Great Moderation and the Great Inflation sample; credit spread shocks were significantly larger over the Great Inflation period and the sample including the Great Recession compared to the Great Moderation sample. This clearly supports the use of a VAR model which accounts for both time variation in the parameters and stochastic volatility. In what follows, we present detailed results from the TV-VAR.

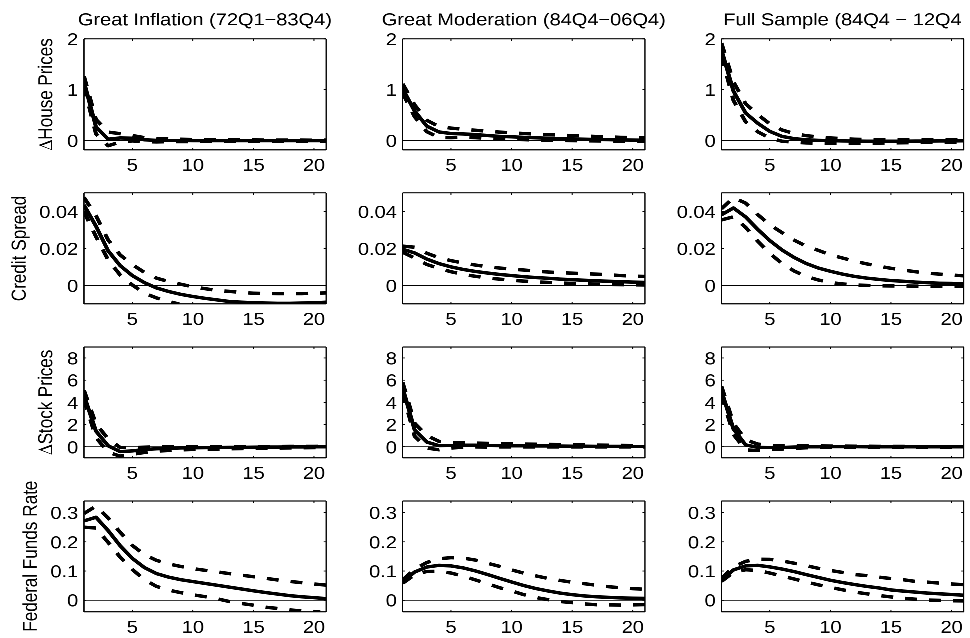
[1] We estimate the constant parameter VAR using Bayesian methods, assuming an independent Normal-Wishart prior along the lines of Koop and Korobilis (2010). To calibrate the prior hyperparameters we use the corresponding OLS quantities estimated over a training sample of 60 quarters.

Figure 8: **Impulse response functions from C-VARs estimated over different subsamples**

(a) Response of ΔGDP to financial and FFR shocks



(b) Response of financial variables and the FFR to own shock

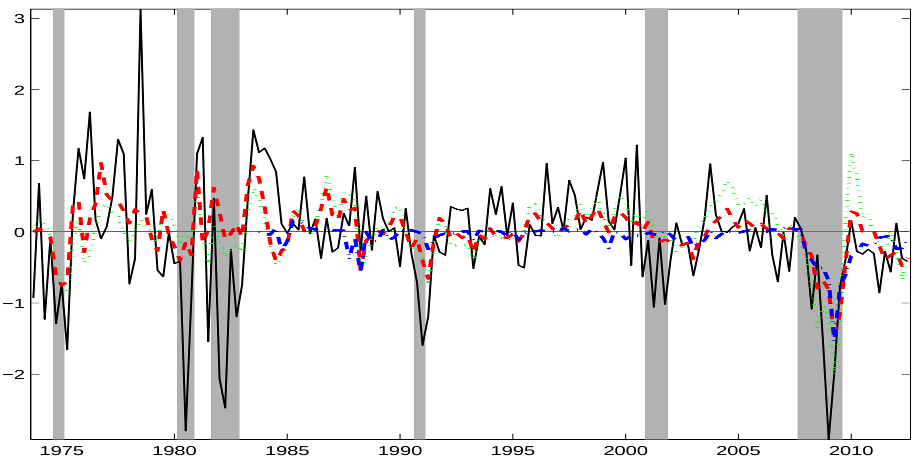


Notes: This figure shows the median and the 1 standard deviation percentile of the impulse responses obtained from constant parameter VARs estimated over different subsamples. Panel (a) shows the median and one standard deviation percentiles of the impulse responses of GDP growth to unit shocks to house prices, credit spreads, stock prices and the Federal Funds rate. Panel (b) shows the median and one standard deviation percentiles of the impulse responses of house prices, credit spreads, stock prices and the Federal Funds rate to their own shock with size of one standard deviation.

7 Time-varying parameter VAR including the NFCI

In the main text we assess the benefit of exploiting lots of financial time series by replacing house price inflation, stock price inflation and credit spreads with the NFCI published by the Federal Reserve Bank of Chicago. In the main text we show the results from a constant parameter VAR. Here we document that estimating the NFCI-VAR in a time-varying parameter setting yields qualitatively similar results: Financial conditions still drag down the economy after the Great Recession, corroborating the finding obtained from the baseline TV-VAR and the constant parameter VAR including the NFCI.

Figure 9: **Overall contribution of financial shocks - different models**



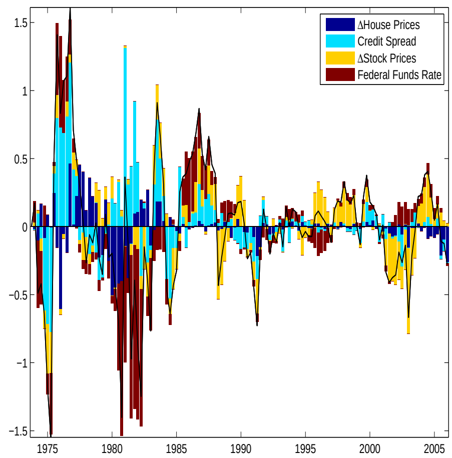
Notes: The black line corresponds to GDP growth. The red dashed line corresponds to the contribution of house prices, credit spread and stock prices shocks to GDP growth obtained from the time-varying parameter VAR. The green dotted line corresponds to the contribution of house prices, credit spread and stock prices shocks to GDP growth obtained from a constant parameter VAR. The blue dash-dotted line corresponds to the contribution of the NFCI shock to GDP growth obtained from time-varying parameter VAR including GDP growth, inflation, NFCI and the Federal Funds rate. Otherwise see Figure 1 in the main text.

8 Real-time properties of the model

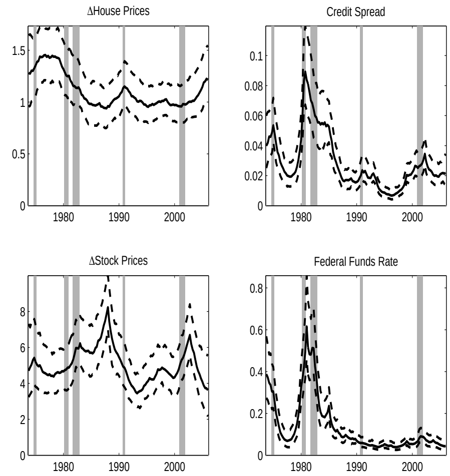
To assess the real-time properties of our baseline model and whether the data revision process was relevant around the crisis period, we collect real-time data on GDP growth and inflation for three vintages 2005Q4, 2007Q4 and 2009Q4 from the Federal Reserve Bank of Philadelphia's Real Time database. For each vintage we compare the results with those obtained with the final data for the corresponding subperiod (where the final data for us coincide with those used for the full sample analysis).

The main results are reported in Figure 10. Using real-time data until the end of 2005 or until the end of 2007, the model would have already revealed a rise in the house price shock volatility at the end of the sample, but no positive contribution of house price shocks in the pre-crisis period. In general, the importance of house price shocks does not appear to be as large as in the model estimated over the full sample. Had we used data ending in 2009Q4, the model would have shown mild positive contributions of house price shocks during the pre-crisis period and a strong rise in the volatility. For the crisis period the model shows large negative contributions of both house price and credit spread shocks to GDP growth. This suggests that it was hard to fully understand house price dynamics and its real effects with only data available up to the crisis. However, once the crisis broke out, the model would have been helpful in detecting its origins. We also compared the results with those obtained with the final data for the corresponding subperiod. The results from this exercise are similar to those using real-time data. Hence, it seems that it is not the data revision process which makes it difficult to fully detect the sources of the crisis but the missing information which is revealed by the crisis.

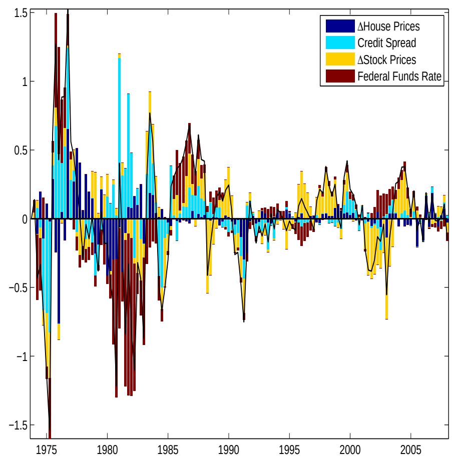
Figure 10: **Real-time analysis**



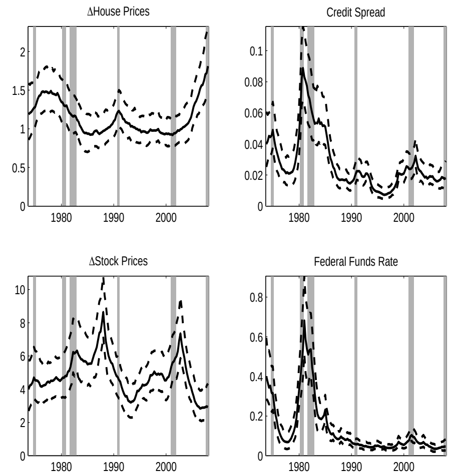
(a) Shock decomposition 05Q4 vintage



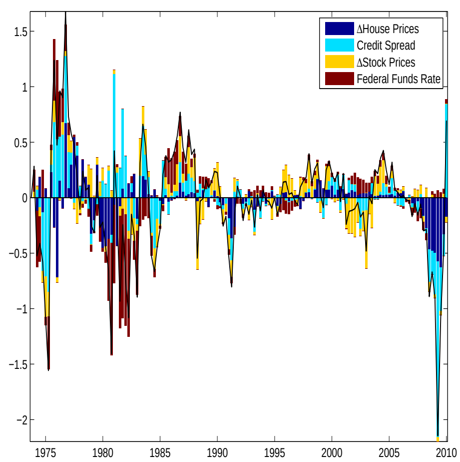
(b) St.dev. of structural shocks 05Q4 vintage



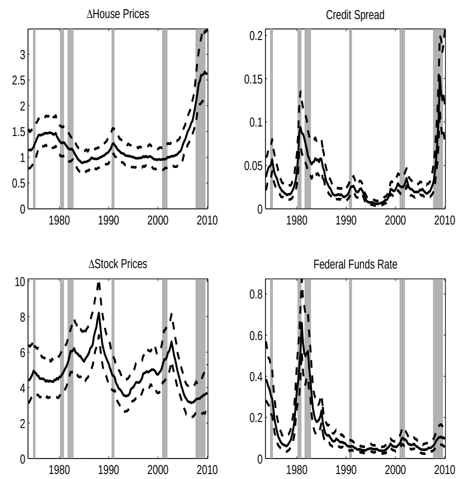
(c) Shock decomposition 07Q4 vintage



(d) St.dev. of structural shocks 07Q4 vintage



(e) Shock decomposition 09Q4 vintage



(f) St.dev. of structural shocks 09Q4 vintage

Notes: See notes to Figures 3 and 6.

9 Robustness with respect to the identification scheme

In this section we analyze robustness of our results with respect to the identification scheme. First, we consider three alternative orderings for the fast-moving financial variables and the monetary policy instrument in the baseline TV-VAR. Next, we evaluate combined long-run/short-run zero restrictions and combined short-run zero/sign restrictions to address recent empirical evidence that employing zero contemporaneous restrictions to identify financial shocks might produce misleading results.[2]

Alternative Cholesky orderings

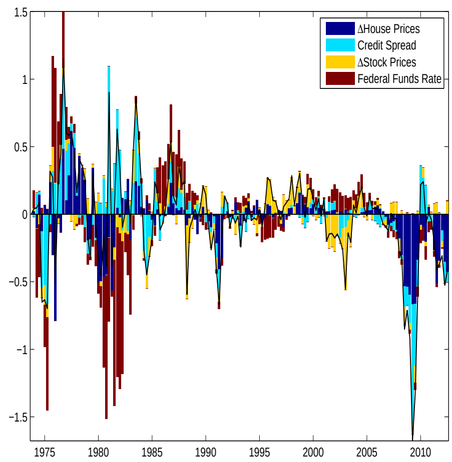
Starting with the alternative orderings, the first one we use is: Federal Funds rate $\rightarrow$ credit spread $\rightarrow$ stock price inflation. This ordering implies that the Federal Funds rate responds with a delay to shocks to credit spreads and the stock market, which may be seen as a plausible assumption, given that monetary policy decisions are typically taken every six weeks (Swiston (2008)). The other ordering we consider is: stock price inflation $\rightarrow$ credit spread $\rightarrow$ Federal Funds rate, i.e. we switch the ordering between stock price inflation and the credit spread. Finally, we consider Federal Funds rate $\rightarrow$ credit spread $\rightarrow$ stock price inflation.

We plot the results of these exercises in Figures 11 - 13. Results are in general remarkably similar to those out of the baseline model. The only result worth 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. 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. Indeed, stock market wealth has dropped by 50 percent between 2007Q3 and 2009Q1 (see Hubrich and Tetlow (2015)) so that negative stock market wealth effects cannot be excluded.

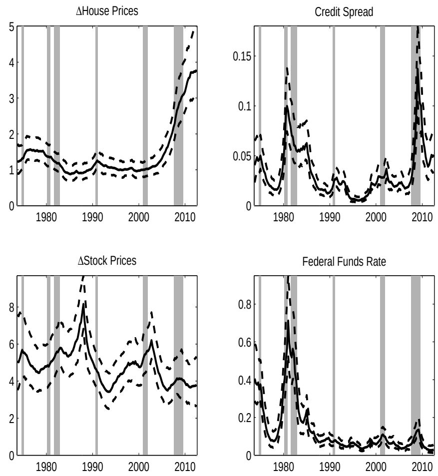
[2] We thank an anonymous referee for suggesting this to us.

Figure 11: **Results from alternative ordering I**

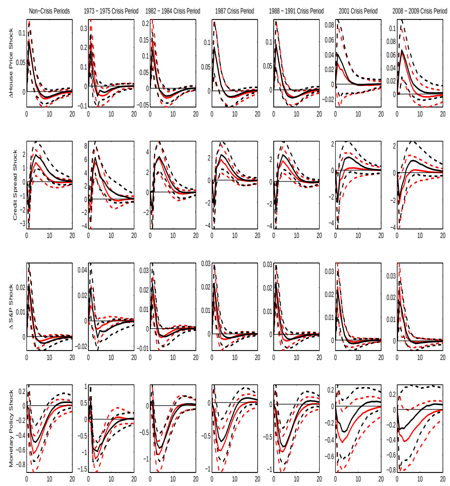
(a) Historical decomposition



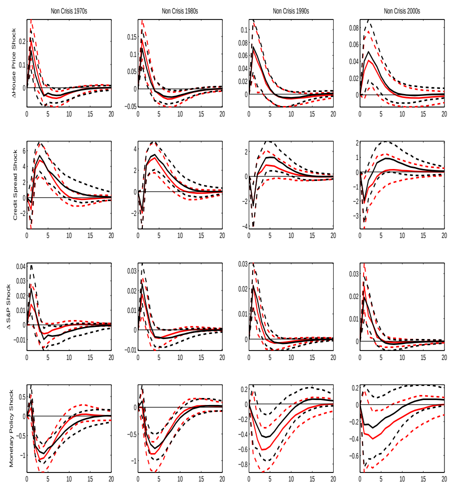
(b) St.dev. of structural shocks



(c) IRFs crisis



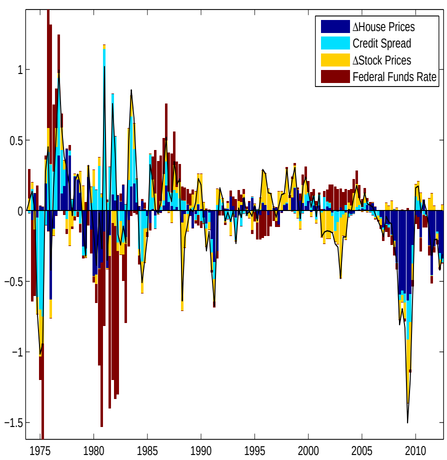
(d) IRFs non-crisis



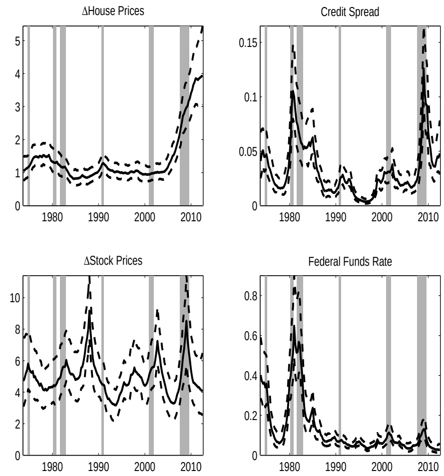
Notes: This Figure shows results from a time-varying parameter VAR in which the ordering in the financial block is: house price inflation - Federal Funds rate - credit spreads - stock price inflation

Figure 12: **Results from alternative ordering II**

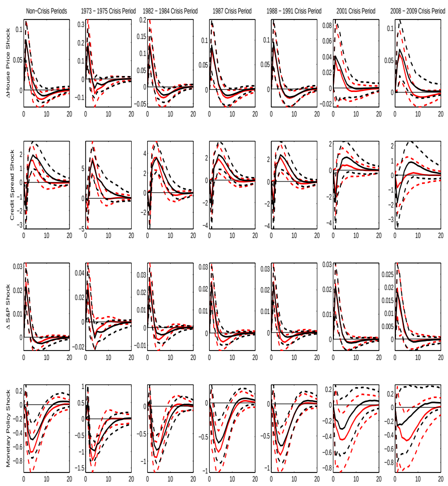
(a) Historical decomposition



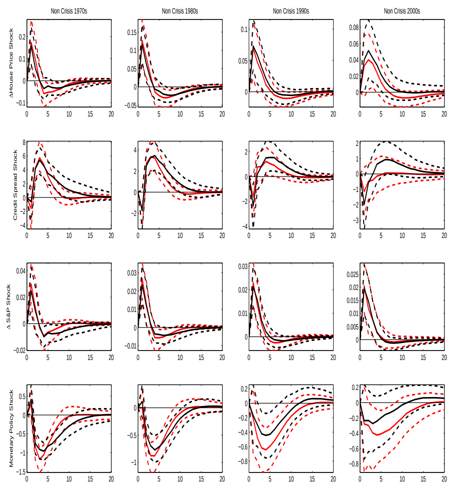
(b) St.dev. of structural shocks



(c) IRFs crisis



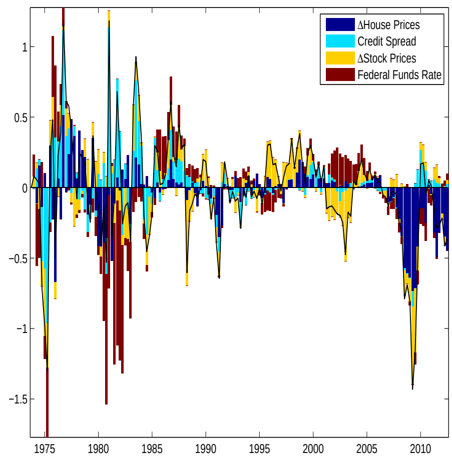
(d) IRFs non-crisis



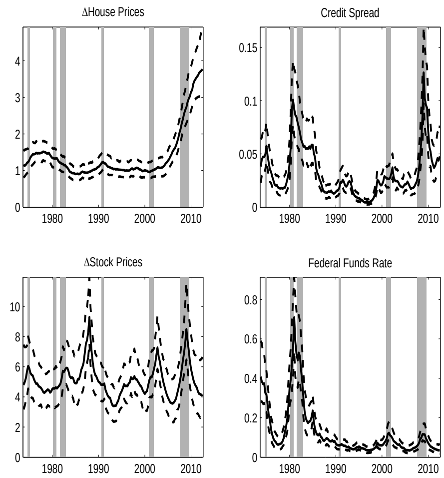
Notes: This Figure shows results from a time-varying parameter VAR in which the ordering in the financial block is: house price inflation - Federal Funds rate - stock price inflation - credit spreads

Figure 13: **Results from alternative ordering III**

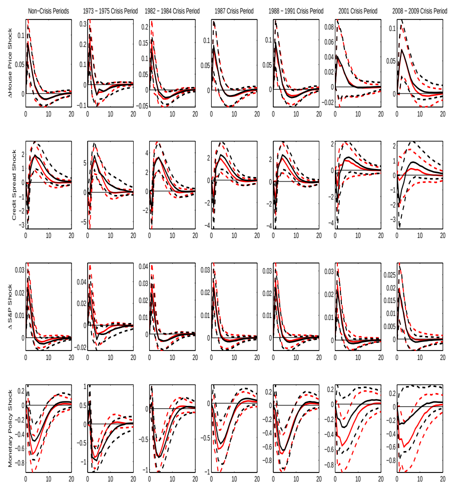
(a) Historical decomposition



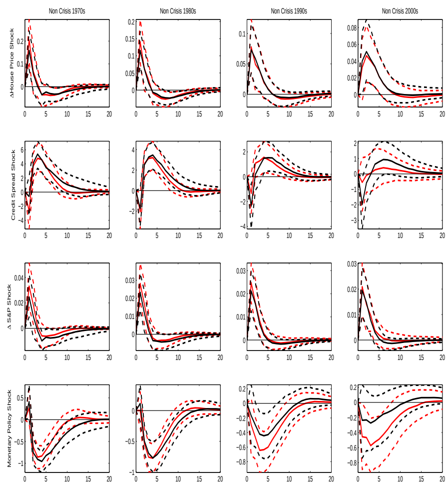
(b) St.dev. of structural shocks



(c) IRFs crisis



(d) IRFs non-crisis



Notes: This Figure shows results from a time-varying parameter VAR in which the ordering in the financial block is: house price inflation - stock price inflation - credit spreads - Federal Funds rate

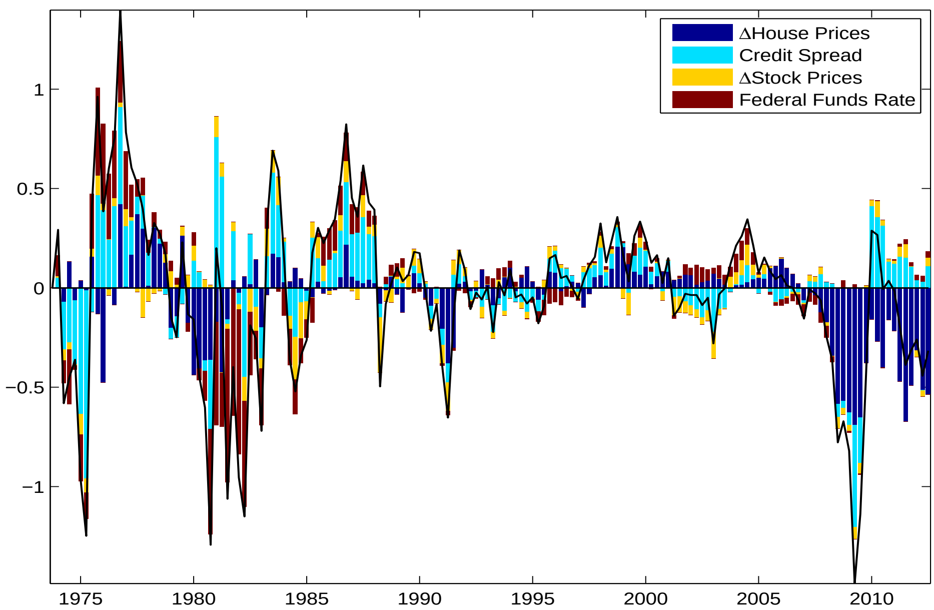
Combined short-run/long-run zero restrictions

Moving to the combined long-run/short-run zero restrictions, we adopt identifying restrictions that are established in the literature. We follow Bjoernland and Leitemo (2009) and allow for mutual contemporaneous interaction between the Federal Funds rate and the stock price. This is achieved by replacing the zero short-run restriction of the Federal Funds rate shock on stock price inflation with the restriction that Federal Funds rate shocks do not have long-run effects on stock prices. We additionally relax the short-run restriction between the credit spread and stock prices by imposing the restriction that stock price shock do not have long-run effects on GDP. As argued by (and consistent with) Lütkepohl and Velinov (2014), stock prices are driven by both, fundamentals (related to GDP, technological progress etc.) and speculation, and we identify a stock price shock here as a non-fundamental shock which does not have a permanent effect on GDP. Allowing for contemporaneous feedback effects between credit spreads and stock prices seems particularly important because spreads and stock prices react both instantaneously to shocks in financial markets. Otherwise we leave the identification scheme as in our baseline model.

Results from this identification scheme are presented in Figure 14. Overall, results are very similar to those from the baseline identification scheme. In both models the signs of the impulse responses are identical, and shapes, magnitudes and statistical significance are very similar. Especially for the period after 2000, which is the focus of our analysis, results for both identification schemes are basically identically.

Figure 14: **Results from combined short-run/long-run restrictions**

(a) Historical decomposition



(b) Standard deviation of structural shocks

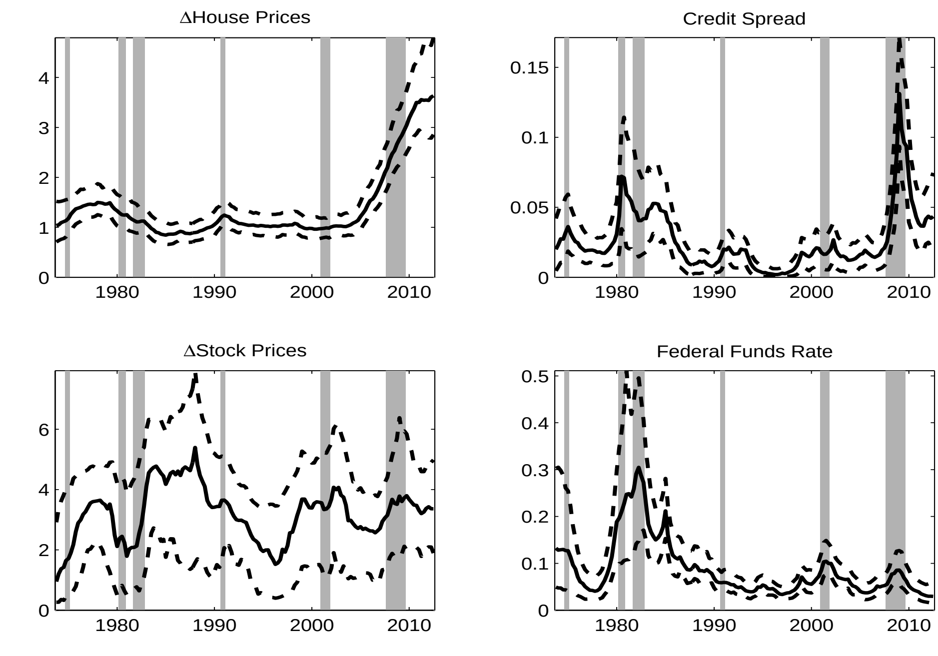
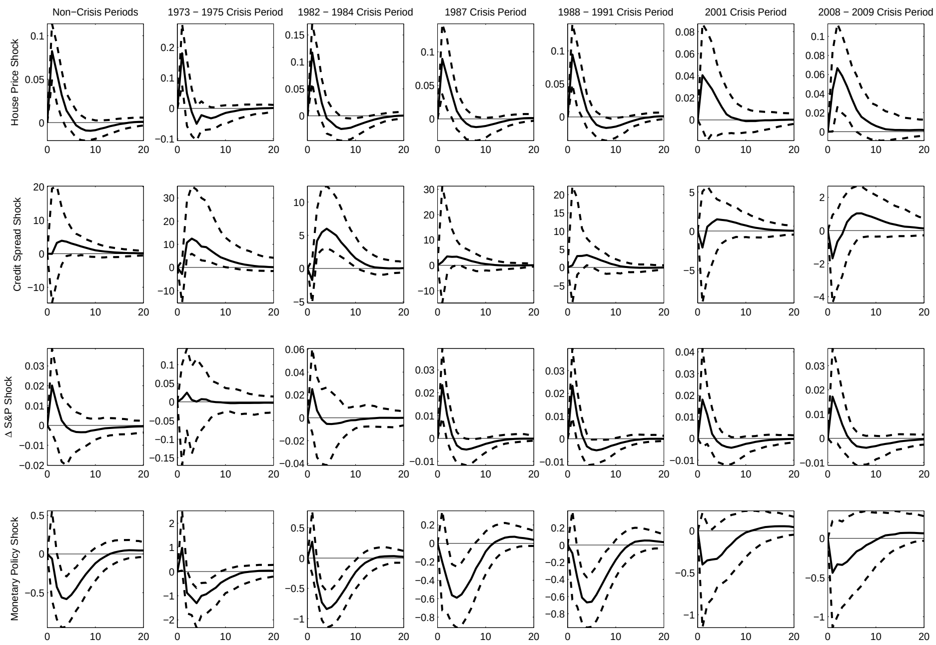
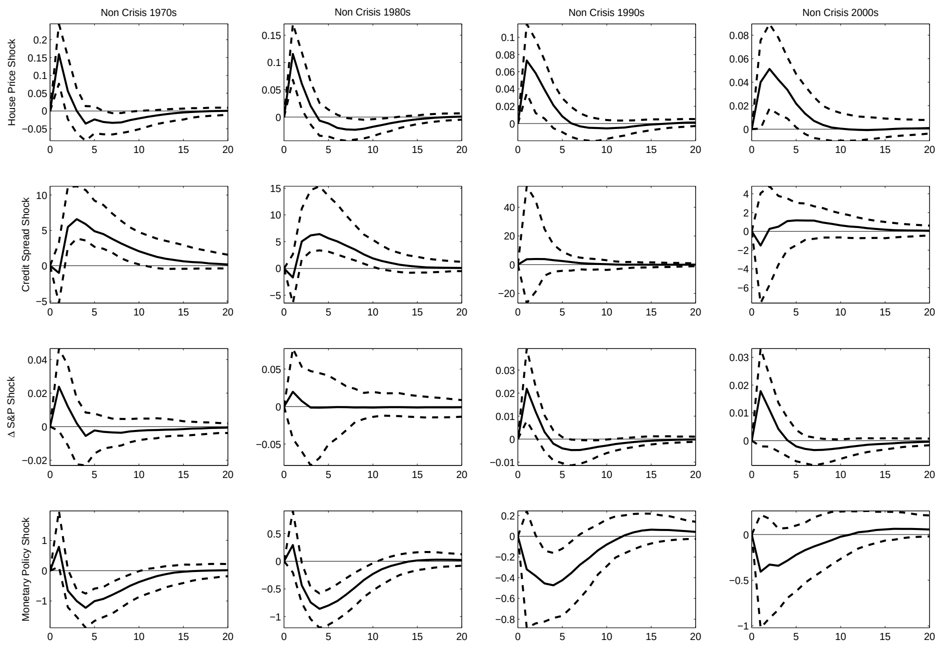


Figure 14: **continued - Results from combined short-run/long-run restrictions**

(c) Impulse responses financial crisis vs. non-crisis periods



(d) Impulse responses non-crisis periods



Notes: This figure shows results from a time-varying parameter VAR identified using a combination of short-run/long-run zero restriction that allows for mutual interaction between stock price inflation and the Federal Funds rate and between stock price inflation and the credit spread. Otherwise see notes to Figures 3, 5 and 8

Combined short-run zero/sign restrictions

We move on to the combined zero and sign restrictions, which we impose on impact and which are outlined in Tables 1 and 2. We adopt two alternative schemes, which both allow for contemporaneous interaction between credit spreads, the stock price and the monetary policy interest rate.

Within both schemes we formally identify three shocks disentangled from macroeconomic shocks: a "housing shock", a "financial market shock" and a "monetary policy shock". The housing shock is associated with an increase in house prices. The financial market shock is associated with an increase in the stock price and a reduction in the credit spread. We have a fourth residual shock within the financial block, which is restricted not to satisfy the same restrictions as the other shocks and which absorbs all other shocks in the system (see, e.g., Canova et al. (2007)). Macroeconomic variables are still treated as slow-moving variables, which is standard in the literature (see, e.g., Jarocinski and Smets (2008), Gilchrist and Zakrajsek (2012), Buch et al. (2014), Bruno and Shin (2015) and Ciccarelli et al. (2014)).

The first scheme (Identification scheme based on short-run zero/sign restrictions I in the table) treats house price growth (together with GDP growth and inflation) as a slow-moving variable, consistent with our robustness analysis in which we alter the Cholesky ordering of credit spreads, the monetary policy rate and stock price growth only. As before, the house price can respond only after a delay to shocks to the latter three variables, which disentangles the housing shock from monetary policy and financial market shocks. GDP growth and inflation, by contrast, can now respond on impact to the housing shock. The housing shock is identified as a demand shock, which we disentangle from an aggregate demand shock by imposing the restriction that the house price moves by more than the general price level (the opposite would hold for an aggregate demand shock). The results from this identification scheme are shown in Figure 15.

The second scheme (Identification scheme based on short-run zero/sign restrictions II) allows the house price to react contemporaneously to monetary policy shocks and the residual shock, which is less restrictive than with our baseline identification scheme. However, we still impose a zero restriction on the impact effect on the house price of the financial market shocks, which we need in order to disentangle housing from financial market shocks. While financial and housing shocks are assumed to act as demand shocks and, consequently, move the policy interest rate and asset prices in the same direction[3], monetary policy shocks move them in opposite directions. We show the results in Figure 16

Our main messages remain broadly unchanged compared to those obtained with the baseline model. Specifically, the shapes of the impulse responses to the housing, financial market and monetary policy shocks and their size (computed as impact effects on the house price, the Federal Funds rate and the credit spread) look very similar to those of the baseline model's house price, credit spread and Federal Funds rate shocks, respectively.

There are, however, a few interesting differences. The first scheme based on combined zero and sign restrictions (unsurprisingly) yields effects of the housing shock on GDP growth that are more frontloaded. Consequently, the historical decomposition reveals that the housing shock makes somewhat larger contributions to growth compared to the baseline model's contributions. The second scheme leads to less significant reactions of GDP growth to the housing shocks in the 1980s, 1990s and the 2000s up until the Global Financial Crisis. An explanation might be that the first VAR which treats house price growth, jointly with GDP growth and inflation, as a slow-moving variable attributes more weight to the fundamental component of the house price (and of the housing shock). By contrast, the second VAR which allows the house price to react instantaneously to monetary policy shocks (and the residual shock) emphasizes the fast-moving, perhaps non-fundamental, component more. Our findings suggest that the former component has larger effects on growth than the latter. However, even in the second identification scheme housing shocks are still the main financial determinant of GDP growth during the latter crisis.

In both schemes, financial market shocks display larger effects (and the overshooting is larger as well) than credit spread shocks from the baseline model. The main reason

[3]Iacoviello and Neri (2010) find that positive housing preference shocks trigger a rise in house prices and interest rates. Moreover, most theoretical general equilibrium models imply that expansionary financial (credit supply) shocks have demand effects and lead to a rise in the interest rate, see, e.g., Gertler and Karadi (2011), Curdia and Woodford (2010), Gilchrist and Ortiz (2009). For other views see Gerali et al. (2010), Atta-Mensah and Dib (2008).

is that we have defined financial market shocks as shocks that affect both credit and stock markets negatively, whereas credit spread shocks are generally found to trigger an insignificant reaction of stock prices in the baseline model. In the second identification scheme based on sign restrictions, the historical decomposition suggests that financial market shocks indeed pick up both credit spread and stock price shocks from the baseline model: we find notable contributions during the stock market busts in 1987 and around 2001, but also in periods in which recursively identified credit spread shocks previously dominated. In both schemes, monetary policy shocks have less persistent effects, and a prize puzzle never occurs. They contribute to GDP growth a bit less in the early-1980s and a bit more over the most recent decade. Another interesting observation is that, unlike in the baseline model, the effects of monetary policy shocks on GDP growth have not become weaker over time. The literature has indeed not yet come to a consensus on the time-varying effects of monetary policy, see Table A.2 in Eickmeier et al. (2015).

Overall we conclude that our main results are robust with respect to the identification scheme used.

Table 1: Identification scheme based on short-run zero/sign restrictions I

	Housing	Financial Market	Monetary Policy
GDP growth	+	0	0
Inflation	+	0	0
ΔHouse Prices	+	0	0
Credit Spread		-	+
Δ Stock Prices		+	-
Federal Funds Rate		+	+
Inflation - ΔHouse Prices	-		

Notes: Restrictions are imposed only on impact. We have also identified aggregate supply and demand shocks. Supply shocks raise GDP growth and lower inflation. Demand shocks raise GDP growth, inflation and inflation-house price growth. This helps us to better identify housing shocks (see e.g. Matthias (2007)).

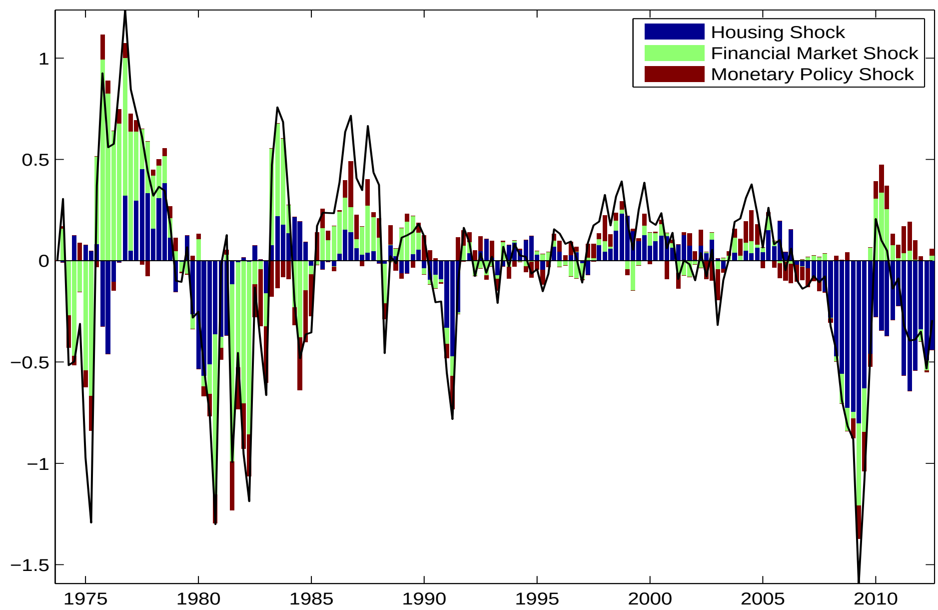
Table 2: Identification scheme based on short-run zero/sign restrictions II

	Housing	Financial Market	Monetary Policy
GDP growth	0	0	0
Inflation	0	0	0
ΔHouse Prices	+	0	-
Credit Spread		-	
Δ Stock Prices		+	
Federal Funds Rate	+	+	+

Notes: Restrictions are imposed only on impact.

Figure 15: **Results from combined short-run zero/sign restrictions I**

(a) Historical decomposition



(b) Standard deviation of structural shocks

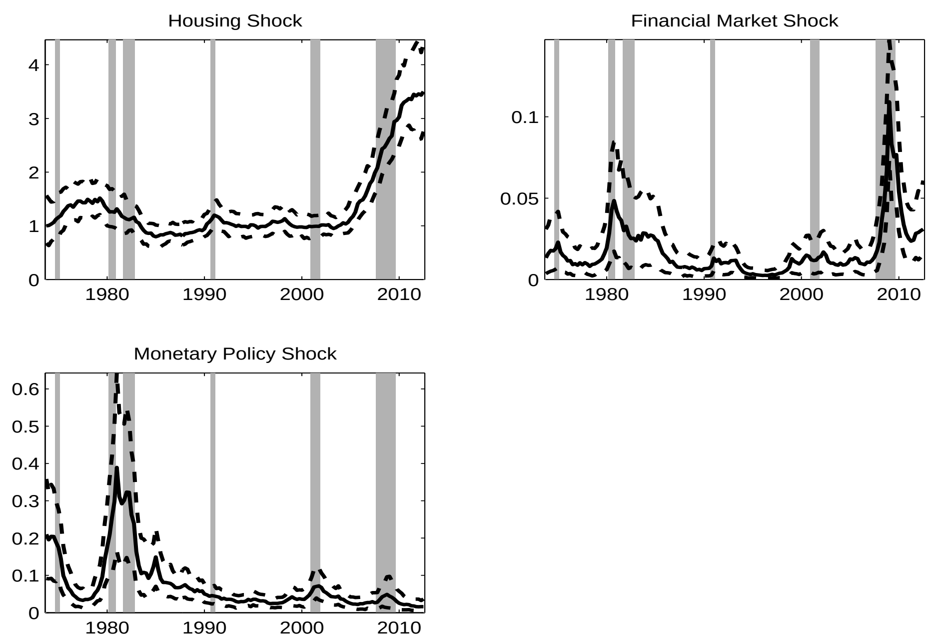
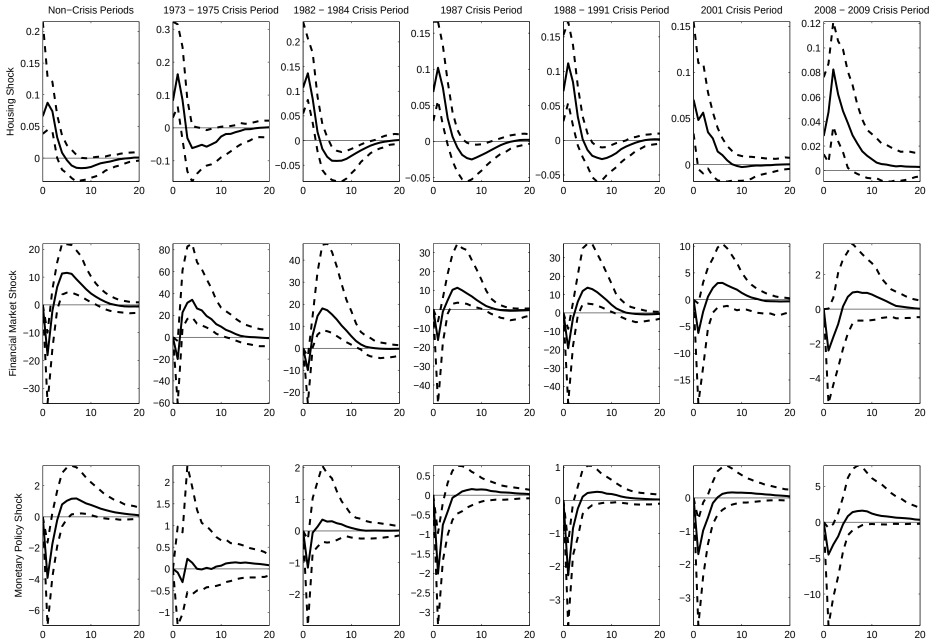
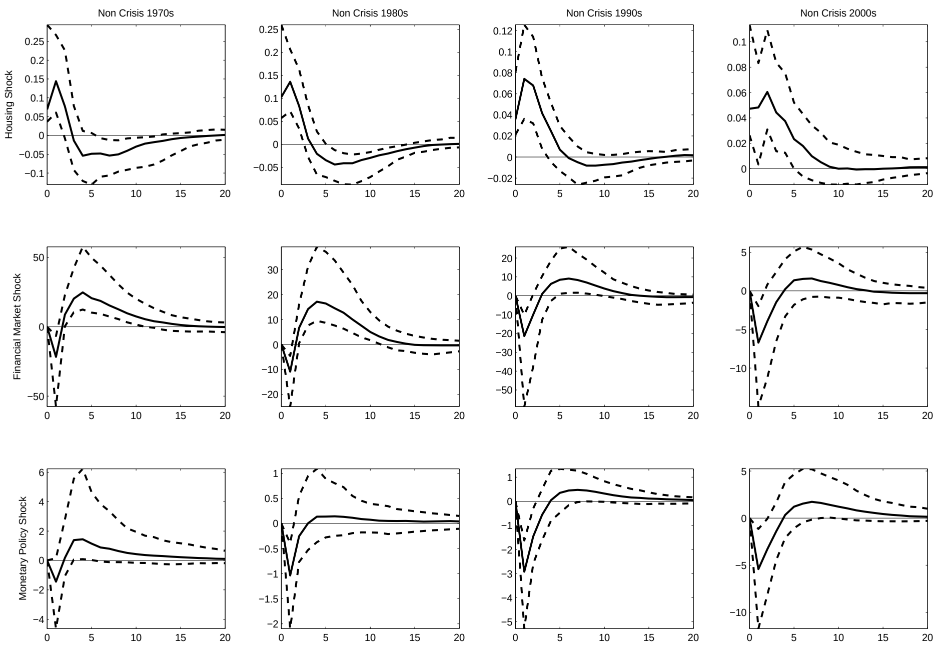


Figure 15: **continued - Results from combined short-run zero/sign restrictions I**

(c) Impulse responses financial crisis vs. non-crisis periods



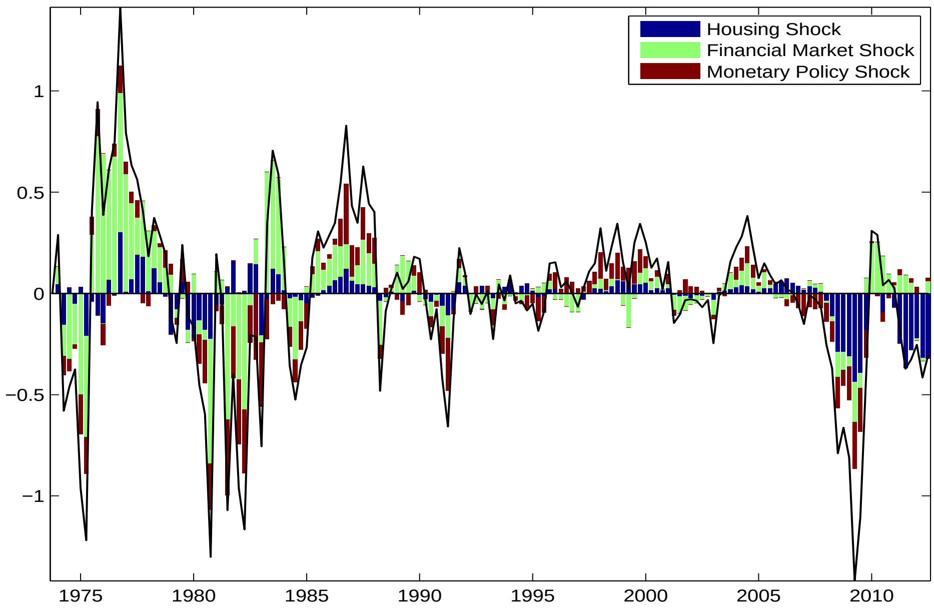
(d) Impulse responses non-crisis periods



Notes: This figure shows results from a time-varying parameter VAR identified using a combination of restrictions on the signs of impulse responses and zero contemporaneous restrictions. See Table 2 for an overview of the identifying restrictions. Otherwise see notes to Figures 3, 5 and 8. In Figure 14 (a) the black line includes the contribution of the residual shock.

Figure 16: **Results from combined short-run zero/sign restrictions II**

(a) Historical decomposition



(b) Standard deviation of structural shocks

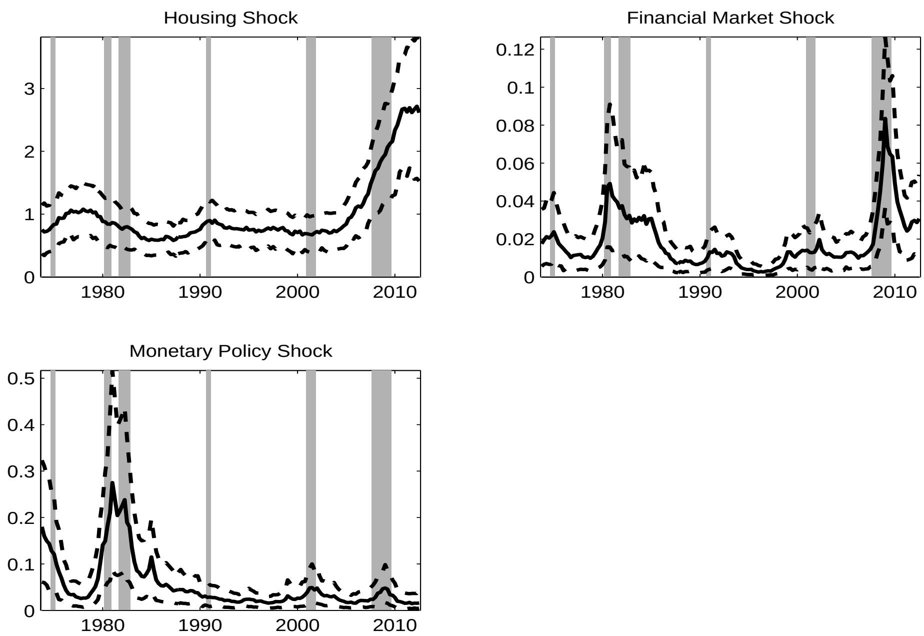
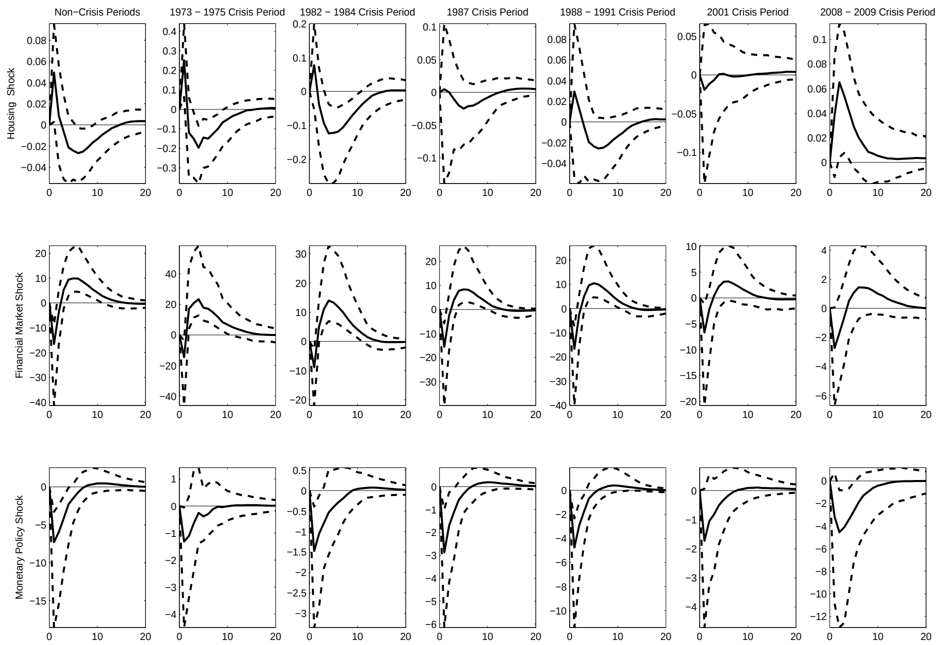
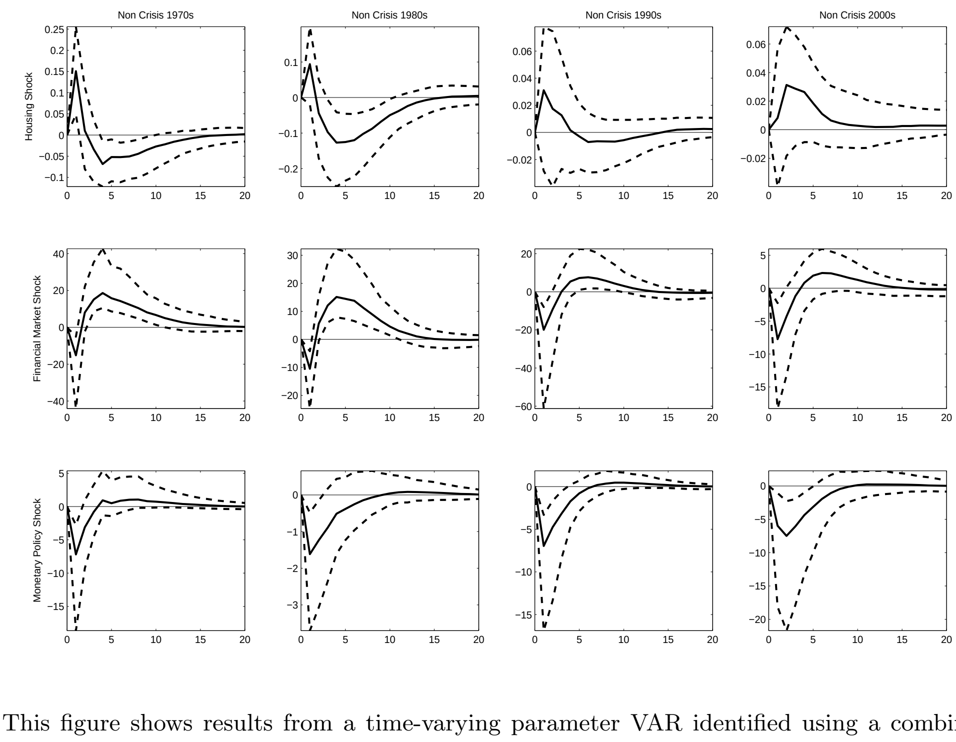


Figure 16: **continued - Results from combined short-run zero/sign restrictions II**

(c) Impulse responses financial crisis vs. non-crisis periods



(d) Impulse responses non-crisis periods



Notes: This figure shows results from a time-varying parameter VAR identified using a combination of restrictions on the signs of impulse responses and zero contemporaneous restrictions. See Table 3 for an overview of the identifying restrictions. Otherwise see notes to Figures 3, 5 and 8. In Figure 15 (a) the black line includes the contribution of the residual shock.

10 Overview of related literature

Table 3: **Overview on the empirical literature on time-varying macro-financial linkages**

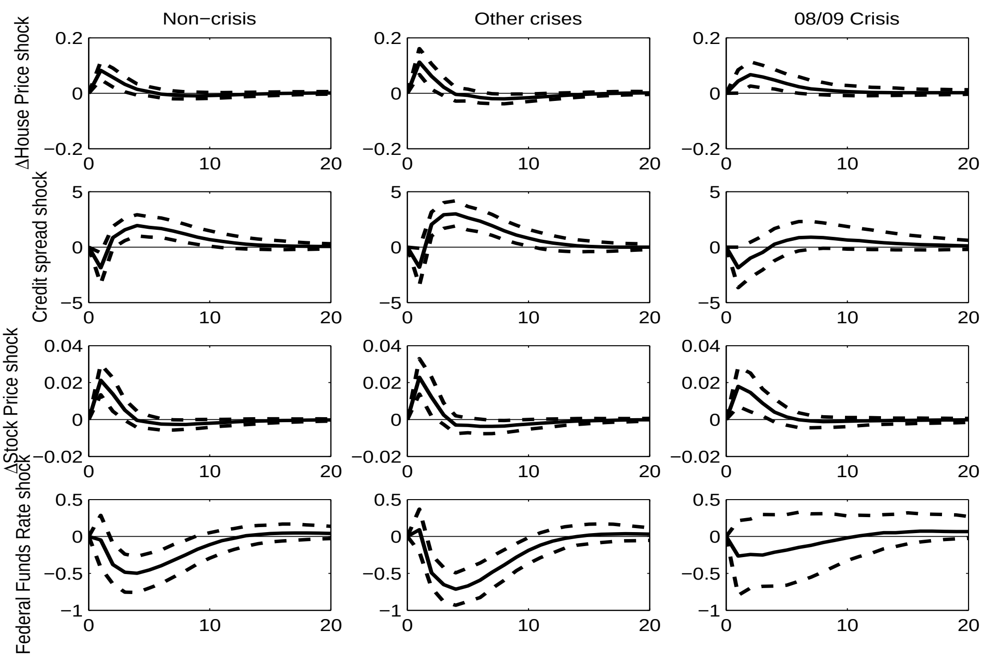
Notes: In the VAR applications, which look at shocks to a financial conditions or a financial stress index, the index is counted as one variable. The indexes are, however, typically formed of a large number of financial variables.

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	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
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
Nason/Tallman (2012)	VAR (7 variables)	Coefficients, 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. (2012)	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	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,	GIRFs	1980-2011	10 advanced countries	No changes in the transmission.

11 Additional results from the baseline model

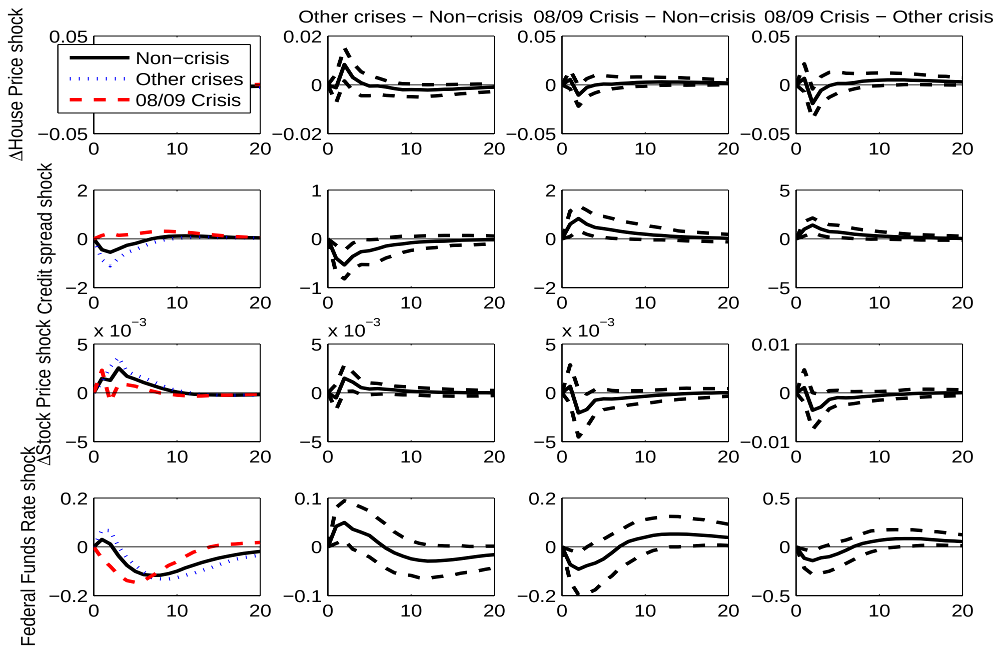
In Figure 17 we show the impulse responses averaged over the periods defined in the main text together with one standard deviation percentile. In Figure 18 we show averages impulse responses of inflation to each individaul financial shocks and differences between them. Figure 18 reproduces Figure 7 in the main text for inflation. Finally, Figure 19 shows the impulse response of inflation averaged over selected periods together with one standard deviation percentiles

Figure 17: **Impulse responses of GDP growth - averages over selected periods**



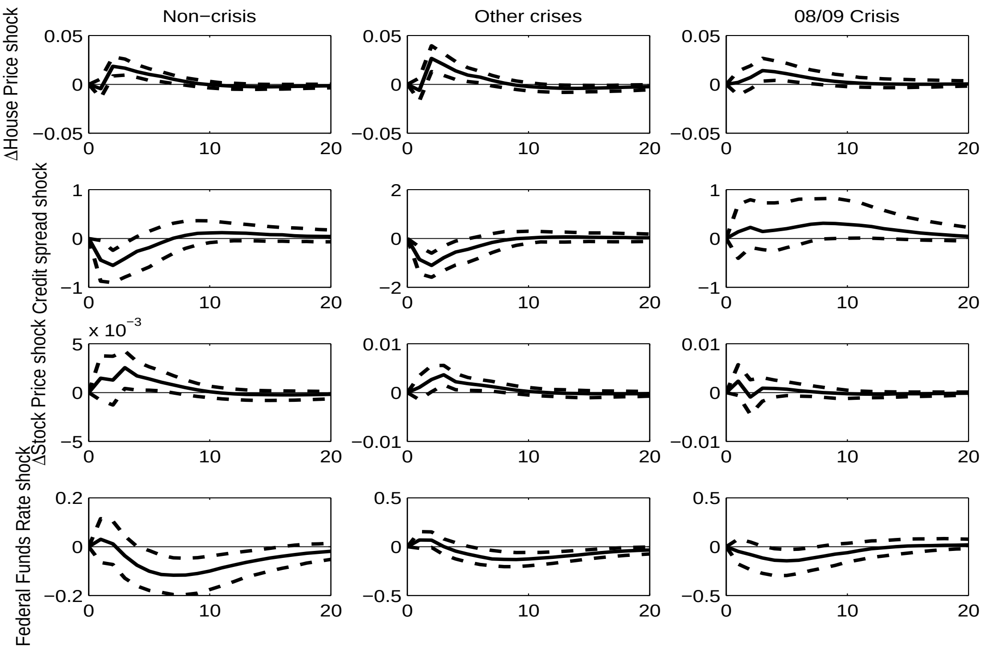
Notes: This figure shows the median and the 1 standard deviation percentile of the impulse responses obtained from the time-varying parameter VAR. Panel (a) shows impulse responses of GDP growth to unit shocks to house prices, credit spreads, stock prices and the Federal Funds rate averaged over the crisis periods as defined in the main text. Panel (b) shows impulse responses of GDP growth to unit shocks to house prices, credit spreads, stock prices and the Federal Funds rate averaged over non-crisis periods.

Figure 18: **Impulse responses of inflation - averages over selected periods and differences**



Notes: This figure shows the median and the 1 standard deviation percentile of the impulse responses obtained from the time-varying parameter VAR. Panel (a) shows impulse responses of GDP growth to unit shocks to house prices, credit spreads, stock prices and the Federal Funds rate averaged over the crisis periods as defined in the main text. Panel (b) shows impulse responses of GDP growth to unit shocks to house prices, credit spreads, stock prices and the Federal Funds rate averaged over non-crisis periods.

Figure 19: **Impulse responses of inflation - averages over selected periods**



Notes: This figure shows the median and the 1 standard deviation percentile of the impulse responses obtained from the time-varying parameter VAR. Panel (a) shows impulse responses of GDP growth to unit shocks to house prices, credit spreads, stock prices and the Federal Funds rate averaged over the crisis periods as defined in the main text. Panel (b) shows impulse responses of GDP growth to unit shocks to house prices, credit spreads, stock prices and the Federal Funds rate averaged over non-crisis periods.

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