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Identification of financial factors in economic fluctuations*

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Abstract

We estimate demand, supply, monetary, investment and financial shocks in a VAR identified with a minimum set of sign restrictions on US data. We find that financial shocks are major drivers of fluctuations in output, stock prices and investment but have a limited effect on inflation. In a second step we disentangle shocks originating in the housing sector, shocks originating in credit markets and uncertainty shocks. In the extended set-up financial shocks are even more important and a leading role is played by housing shocks that have large and persistent effects on output.

JEL Classification: C11, C32, E32.

Keywords: VAR, sign restrictions, financial shocks, external finance premium, housing, uncertainty.

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An important role for shocks originating in the financial sector has been highlighted in the aftermath of the Great Recession. In particular, Christiano *et al.* (2014) have shown that the use of financial variables in the estimation of a Dynamic Stochastic General Equilibrium (DSGE) model with financial frictions is crucial to identify the primacy of financial shocks and to distinguish them from more traditional investment shocks (cf. Justiniano *et al.*, 2010).

The objective of our paper is to quantify the importance of shocks originating in the financial sector in the context of a Vector Autoregression (VAR) identified with a minimum set of sign restrictions and estimated on US data. As in recent DSGE models, financial shocks coexist in our model with supply, demand, monetary and investment shocks. However, the advantage of using a structural VAR is that we do not impose the tight cross-equation restrictions that are a defining feature of DSGE models. Our approach is less grounded on theory but potentially more flexible; it imposes little structure on the data; and, at the same time, can be used to discriminate between models that have different implications for the variables that we may leave unrestricted in the estimation.

We proceed in two steps. In the first step we identify a single financial shock that is consistent with most financial shocks studied in the macroeconomic literature. Our definition of a positive financial shock is simple and intuitive: it is a shock that generates an investment and a stock market boom. These restrictions are consistent with a large series of financial shocks that have been discussed in the literature and that will be reviewed in the next section. Our main result is that financial shocks emerge as important drivers of output, investment and stock prices. Nevertheless, these shocks account only to a limited extent for the fluctuations in prices that are mainly driven by other demand shocks. An important role for financial shocks is able to explain why inflation was low in the pre-Great Recession period and why inflation did not fall much in the aftermath of the Great Recession. The fact that financial shocks are non-inflationary is consistent with the evidence in Christiano *et al.* (2010), who document that inflation is always low during stock market booms in post-war US data. Notably, the shock generates a countercyclical response in the external finance premium in keeping with any meaningful definition of a financial shock.

In the second step we disentangle our general financial shock into different components. In particular, we investigate whether financial shocks originate in the housing sector, in credit markets, or whether they simply capture the importance of uncertainty shocks (cf. Bloom, 2009). In a first experiment we consider shocks originating in the housing sector and in credit markets that we disentangle by imposing a restriction on the credit-to-real-estate-value ratio. We find a more important role for housing shocks, in particular during the Great Recession, although the role of credit shocks is non-negligible. The housing shock might be related to the housing demand shock in Iacoviello and Neri (2010), whereas the credit shock may be interpreted as a shock to the loan-to-value ratio in models with collateral constraints (cf. Justiniano *et al.*, 2015, and Liu *et al.*, 2013, among others). In a second experiment we consider uncertainty shocks, housing shocks and credit shocks in the same set-up. We disentangle credit and uncertainty shocks by imposing a restriction on the ratio of the excess bond premium (EBP) over a measure of volatility (VIX). We confirm the dominant role for housing shocks and find that shocks originating in credit markets have larger effects than uncertainty shocks whose impact on macroeconomic variables is modest and short-lived. In a third experiment we isolate a credit demand shock from a credit supply shock by using data on mortgage interest rates. The former may capture variations in lending standards whereas the latter may be associated with variations in the leverage constraints for banks, perhaps induced by the process of financial liberalization, as discussed in Justiniano *et al.* (2016). While credit supply shocks turn out to be relatively important in our sample, the role of housing shocks is preserved also in this extended set-up.

This paper belongs to a recent and rich literature that studies financial shocks in time series models. The general financial shock that we identify in the first step shares similarities with the one considered in Fornari and Stracca (2013), who estimate a panel VAR for 21 advanced economies. They use a restriction on the response of the ratio of share prices for companies active in the financial sector to a composite stock market index to disentangle financial shocks from demand and monetary shocks, and find that positive financial shocks lead to an investment boom (thus validating our identifying assumption) and to a non-negligible response of output. They also show that financial shocks explain 12% of GDP variability at a horizon of 24 quarters, a share somewhat lower than our finding for the US. Moreover, they find, as we do, that financial shocks are important not only in crisis periods but also in normal times. The effect on inflation is not clear in their model but it is likely to be affected by the absence of a supply shock that plays a key role in our model.

A large number of papers focus on shocks originating in credit markets and emphasise their importance in explaining the Great Recession but also business cycle dynamics in general.[1] Fewer papers consider shocks originating in the housing market. Walentin (2014b) studies the business cycle effects of shocks to the spread between interest rates on mortgages and government bonds of the corresponding maturity in a VAR identified with exclusion restrictions. He documents an important role for these shocks using data for the US, the UK and Sweden. Jarocinski and Smets (2008) consider housing shocks and credit shocks in the same set-up as in the second step of our estimation exercise. They estimate a Bayesian VAR identified with exclusion restrictions and find that housing shocks have a limited but non-negligible impact on non-housing variables like GDP or consumption, while credit supply shocks are almost irrelevant for business cycle fluctuations. Musso *et al.* (2011) find similar results for the US and extend the analysis to the euro area. Prieto *et al.* (2016) estimate a time-varying VAR on US data over the period 1958-2012 and identify housing shocks together with stock market shocks and credit spread shocks. The three financial shocks together explain a sizeable share of business cycle fluctuations, with a large role for housing shocks as in our model, especially

[1] A partial list includes Gilchrist and Zakrajsek (2012) and Meeks (2012) for VAR analysis with exclusion restrictions, Hristov *et al.* (2012), Peersman (2012) and Peersman and Wagner (2015) for VAR analysis with sign restrictions, Amir Ahmadi (2009) and Gambetti and Musso (2016) for models with time-varying coefficients.

in recent years. Their model features richer dynamics by allowing for time-varying parameters, while our model features a broader set of shocks identified with sign restrictions (rather than exclusion restrictions). The separate identification of financial (credit) and uncertainty shocks is discussed in Caldara *et al.* (2016) who disentangle the macroeconomic implications of the two shocks by using the penalty function approach proposed by Faust (1998) and Uhlig (2005). They find that both financial and uncertainty shocks have robust negative effects on economic activity and a combination of the two shocks fully accounts for the contraction in economic activity and the collapse of the stock market during the Great Recession. Our analysis is similar in spirit but emphasises the important role of shocks originating in the housing sector.

The qualifying contribution of our paper is the identification of financial shocks in the VAR together with the main shocks (demand, supply, monetary and investment) that have been studied in the DSGE literature. Such a large number of shocks differentiate our paper from previous contributions and bring our VAR close to the size of estimated medium-size models as Smets and Wouters (2007). Our second contribution is the identification of housing, credit and uncertainty shocks in the same model. As far as we know, this is the first paper both in the DSGE and in the VAR literature that disentangles the three shocks in the same set-up.

Finally, a side-contribution of the paper concerns the external finance premium, a key variable in DSGE models with financial frictions, that we leave unrestricted in our baseline estimation. In the data the external finance premium is countercyclical. However, there is no consensus on its conditional response to macroeconomic shocks which depends on minor details of the model specification (cf. Christensen and Dib, 2008, De Graeve, 2008, and Carlstrom *et al.*, 2014). Given the conflicting evidence on the conditional response of the external finance premium to shocks in theoretical models, it is surprising that, to the best of our knowledge, there is no empirical evidence on the topic. We find that the external finance premium is countercyclical in response to demand, investment and supply shocks, and procyclical or at best acyclical in response to monetary policy shocks.

The paper is organised as follows. Section 1 describes the econometric model and discusses the identification strategy. Section 2 presents the results for the baseline version of our model. In Section 3 we disentangle housing and credit shocks and we propose two additional extensions to discuss uncertainty and credit supply shocks. In Section 4 we summarise the implications for macroeconomic models emerging from our results. Finally, Section 5 concludes.

1 The Model and the Identification Strategy

Consider the following reduced form VAR model:

$$\mathbf{y}_t = \mathbf{c}_\mathbf{B} + \sum_{i=1}^{P} \mathbf{B}_i \mathbf{y}_{t-i} + \mathbf{u}_t, \tag{1}$$

where $\mathbf{y}_t$ is a $(N \times 1)$ vector containing all N endogenous variables, $\mathbf{c}_\mathbf{B}$ is a $(N \times 1)$ vector of constants, $\mathbf{B}_i$ for $i = 1, ..., P$ are $(N \times N)$ parameter matrices, P represents the number of lags, and $\mathbf{u}_t$ is the $(N \times 1)$ reduced form residual with $\mathbf{u}_t \sim N(0, \mathbf{\Sigma})$, where $\mathbf{\Sigma}$ is the $(N \times N)$ variance-covariance matrix. We estimate the model using Bayesian methods and variables in levels. We specify diffuse priors so that the information in the likelihood is dominant. These priors lead to a Normal-Wishart posterior with mean and variance parameters corresponding to OLS estimates.[2]

Regarding the identification procedure, the prediction error $\mathbf{u}_t$ can be written as a linear combination of structural innovations $\boldsymbol{\epsilon}_t$

$$\mathbf{u}_t = \mathbf{A}\boldsymbol{\epsilon}_t, \tag{2}$$

with $\boldsymbol{\epsilon}_t \sim N(0, \mathbf{I}_N)$, where $\mathbf{I}_N$ is an $(N \times N)$ identity matrix and where $\mathbf{A}$ is a non-singular

[2]The Bayesian approach is based on the likelihood function which follows a Gaussian distribution regardless of the presence of nonstationarity and therefore does not need to take special account of nonstationarity (cf. Sims, Stock, and Watson, 1990, and Sims and Uhlig, 1991). Additional details on the Bayesian estimation of the VAR are provided in the Online Appendix (Section A).

parameter matrix. The variance-covariance matrix has thus the following structure $\mathbf{\Sigma} = \mathbf{A}\mathbf{A}'$. As the variance covariance matrix is symmetric, $N(N-1)/2$ further restrictions are needed to derive $\mathbf{A}$ from this relationship.

One popular way of imposing the required restrictions on $\mathbf{A}$ is to use the Cholesky decomposition. In this identification procedure the parameter matrix $\mathbf{A}$ is restricted to be lower triangular, thus implying a recursive identification scheme. Although computationally convenient, the recursive identification cannot be justified theoretically since we include in the estimation some fast-moving variables, such as interest rates, stock prices and other financial variables, cf. Rigobon and Sack (2003) and Bjørnland and Leitemo (2010).[3] This leads us to rely on a mapping from the reduced form innovations to the structural innovations that is based on sign restrictions (cf. Faust, 1998, Canova and De Nicolo', 2002, Peersman, 2005, Uhlig, 2005, and Fry and Pagan, 2011).

We argue that the use of sign restrictions for identification is particularly appropriate in a model with six identified shocks, although challenging from a computational point of view. In fact, one issue with sign restrictions is the so-called "multiple shocks problem", i.e. the fact that the restrictions imposed are potentially consistent with more than one shock (cf. Fry and Pagan, 2011). While particularly relevant when only one shock is identified, the "multiple shocks problem" is arguably less serious in our model with six identified shocks.

To incorporate the sign restrictions we use the algorithm described in Rubio-Ramirez *et al.* (2010) that is particularly efficient when the number of variables included in the system and the number of shocks to be identified are large.[4] The procedure works as follows. In a first step we draw $\mathbf{A}$ using the Cholesky decomposition, producing uncorrelated shocks that correspond to shocks from an exactly identified model. To form combinations of the structural shocks emanating from the recursively identified model, we first perform a QR decomposition

[3] Alternative methods like the use of long-run restrictions or identification through heteroskedasticity seem unfeasible in the context of a model with six shocks.

[4] The estimation is conducted in MATLAB version R2014a using the parallel function over a 12-core machine with 3.55GHz. The estimation is completed in almost one week for models with six identified shocks.

of $\mathbf{X} = \mathbf{QR}$, where $\mathbf{X}$ is a $(N \times N)$ matrix drawn from $\mathbf{X} \sim MN(\mathbf{0}, \mathbf{I}_{N^2})$.[5] Then, we generate candidate impulse responses from $\mathbf{AQ}$ and $\mathbf{B}_i$ for $i = 1, ..., P$ and check if the generated impulse responses satisfy the sign restrictions. If the sign restrictions are not satisfied, we draw a new $\mathbf{X}$ and iterate over the same procedure again until the sign restrictions are satisfied. Those restrictions are imposed only on impact, in keeping with the recommendation of Canova and Paustian (2011), and are summarised in Table 1.

Our assumptions to identify demand, monetary and supply shocks are standard in the literature (cf. Peersman, 2005, and Peersman and Straub, 2006) and are consistent with a simple three-equation New Keynesian model.[6] It is more challenging to separately identify demand, investment and financial shocks. Our strategy is the following: we use data on investment in the estimation of the reduced form model and we restrict the response of the ratio of investment over output. We impose that positive demand shocks have a negative effect on the ratio (notice that investment can still increase in response to these shocks, but less so than the remaining part of aggregate demand), whereas positive investment and financial shocks increase the ratio. This is consistent with the idea that positive investment and financial shocks create investment booms. Importantly, we interpret our demand shock as a shock that affects the components of aggregate demand other than investment: it may capture a fiscal shock, a shock to consumption (discount factor shocks) or a foreign shock.[7] The imposed restrictions are satisfied in standard DSGE models like Smets and Wouters (2007) and Justiniano *et al.* (2010).

The use of data on investment enables us to identify the demand shock, but we need an additional variable to disentangle investment shocks from financial shocks. To achieve this

[5] $MN(\mathbf{0}, \mathbf{I}_{N^2})$ indicates a multivariate normal distribution with mean a $(N \times N)$ matrix of zeros and variance covariance a $(N^2 \times N^2)$ identity matrix.

[6] In addition, we impose the innocuous restriction that an expansionary supply shock must have a positive effect on the stock market. While not strictly necessary for the identification of the supply shock, this restriction allows us to identify a residual shock with an economic interpretation, i.e. as a supply shock that moves output and the stock market in different directions.

[7] We name this disturbance "demand shock" for the sake of simplicity. Notice, however, that monetary, investment and financial shocks are also demand shocks insofar as they move output and prices in the same direction. A more appropriate (but cumbersome) denomination would be "non-investment specific demand shock".

Table 1: *Restrictions in the Baseline Model*

	Supply	Demand	Monetary	Investment	Financial
GDP	+	+	+	+	+
Prices	-	+	+	+	+
Interest Rate	NA	+	-	+	+
Investment/Output	NA	-	NA	+	+
Stock Prices	+	NA	NA	-	+
Spread	NA	NA	NA	NA	NA

The table describes the restrictions used for each variable or ratio (in rows) to identified shocks (in columns) in our VAR. NA indicates that the response of the variable is left unrestricted.

goal, we follow closely the discussion in Christiano *et al.* (2014) and we use stock market data. Investment shocks are shocks to the supply of capital and, therefore, imply a negative co-movement between the stock of capital (together with investment and output) and the price of capital. The price of capital is seen as a proxy of the stock market value for the firm and as a main driver of the firm's net worth. Financial shocks, instead, are shocks to the demand for capital and induce a positive co-movement between output and the price of capital (together with the stock market). Therefore, the value of equity is countercyclical in response to an investment shock. This explains why that shock can be the main source of fluctuations in models that do not include financial variables (as in Justiniano *et al.*, 2010), whereas it loses importance in models that use financial variables as observable.

To summarise, the use of restrictions on investment over output and on the stock market enable us to separately identify demand, investment and financial shocks. A positive financial shock is a disturbance that creates an investment boom and a stock market boom. While it may be possible to find parameterizations that violate our restrictions, the overwhelming majority of financial shocks that have been considered so far in calibrated or estimated DSGE models are consistent with our definition of a financial shock.[8]

[8]Our restrictions are satisfied by the financial/housing shocks discussed in Jermann and Quadrini (2012), Martin and Ventura (2012), Liu *et al.* (2013), Walentin (2014a), Christiano *et al.* (2014), Iacoviello (2015), Ajello (2016), Fuentes-Albero (2016), Rannenberg (2016) and Del Negro *et al.* (2017). Notice, however, that our identifying assumptions are not consistent with the shocks to bank capital considered in Gerali *et al.* (2010) and in Meh and Moran (2010). These shocks move output and inflation in different directions and thus would be considered as supply shocks in our framework.

Nonetheless, financial shocks with large effects on consumption are certainly conceivable, although we could not find an example in the recent DSGE literature. Such a shock would be classified as a demand shock in our set-up, grouped together with the other shocks that we previously mentioned. Furthermore, news shocks about future technology may also move investment, output and the stock market in the same direction, as our identified financial shock. Notice, however, that we assume that a positive financial shock increases prices. In contrast, Barsky *et al.* (2014) provide substantial empirical evidence, based both on VAR and DSGE models, pointing to the fact that positive news shocks generate a substantial decline in prices. While the debate on the effects of news shocks is still open in the literature, the results of Barsky *et al.* (2014) are supportive for our strategy to isolate financial shocks.

Notably, we introduce a measure of the external finance premium as an unrestricted variable in our baseline estimation. This constitutes a validation exercise, as we expect a countercyclical response of the premium to any meaningful financial shock. We use the difference between yields on Baa bonds and the Federal Funds rate as a measure of the spread but we experiment with two alternatives, such as the GZ spread constructed by Gilchrist and Zakrajsek (2012) and the difference between yields on Baa bonds and 10-year government bonds, in the Online Appendix (Section B). We include a sixth shock to match the number of shocks with the number of observables. This is a residual that does not satisfy the restrictions imposed on the other five identified shocks. Although this shock is supposed to capture only the residual dynamics in the system, it has an economic interpretation: it is a supply shock that moves output and the stock market in different directions. The additional restrictions on stock prices allow us to match the number of shocks with the number of observables without imposing any restrictions on the premium's dynamics. In this way, the system is fully identified.

2 Results

In this section we present the results derived from the estimation of our baseline model. A common feature of this section is the tight connection with the DSGE literature that will be in part loosened in the next section, where we will identify several kinds of financial shocks.

The model includes 5 lags and is estimated for the US with quarterly data in levels from 1985 Q1 to 2013 Q2. Since our model has constant coefficients, we prefer to concentrate on a relatively homogenous sample period that includes mainly the Great Moderation. The list of endogenous variables in the baseline model features GDP, GDP deflator as measure of prices, interest rate, investment, stock prices and the spread between Baa bonds and the Federal Funds rate. All variables except the interest rates are expressed in terms of natural logs. The data series used in all the estimation exercises are summarised in Table 11. The baseline model has six identified shocks: supply, demand, monetary, investment, financial and the residual described in the previous section.

In Table 2 we report the contribution of each of the six shocks identified in the baseline model to the forecast error variance of our six variables at three different horizons. The variance decompositions are based at each horizon on the median draw that satisfies the sign restrictions.[9] Two shocks explain the lion's share of fluctuations in macroeconomic variables in our model: supply shocks and financial shocks. While supply shocks are the main drivers of output, financial shocks explain around 40% of the variability in investment and in stock prices. Moreover, they are solid second drivers of output dynamics by explaining on average almost 30% of fluctuations. Financial shocks are important for stock prices, investment and output but not for prices, which are explained mainly by demand shocks. Financial shocks matter also in the long run where they are as important as supply shocks. While such a role for supply

[9] As discussed in Fry and Pagan (2011), a variance decomposition based on the median of the impulse responses combines information stemming from different models and does not necessarily sum to one across all shocks. Our variance decomposition measure is rescaled such that the variance is exhaustively accounted for by our six shocks. In the sensitivity analysis we consider two alternative measures of central tendency in which the variance decomposition does not require any normalization.

factors (mainly labour supply) is often embedded in macroeconomic models, the importance of financial factors for long-run dynamics has been discussed only recently (cf. Borio, 2012).

Table 2: *Median Forecast Error Variance Decompositions for the Baseline Model*

	Horizon	Supply	Demand	Monetary	Investment	Financial	Residual
GDP	1	0.39	0.05	0.07	0.08	0.24	0.16
	5	0.52	0.06	0.03	0.02	0.29	0.08
	20	0.49	0.02	0.07	0.04	0.34	0.04
Prices	1	0.36	0.07	0.11	0.17	0.06	0.22
	5	0.08	0.30	0.13	0.24	0.19	0.06
	20	0.10	0.33	0.16	0.14	0.13	0.13
Interest Rate	1	0.08	0.22	0.16	0.22	0.31	0.00
	5	0.09	0.34	0.14	0.20	0.18	0.04
	20	0.16	0.30	0.13	0.17	0.14	0.09
Investment	1	0.21	0.03	0.08	0.25	0.39	0.05
	5	0.41	0.04	0.04	0.06	0.44	0.01
	20	0.36	0.02	0.06	0.07	0.42	0.07
Stock Prices	1	0.33	0.09	0.00	0.15	0.36	0.07
	5	0.48	0.09	0.01	0.09	0.32	0.01
	20	0.37	0.08	0.02	0.05	0.41	0.06
Spread	1	0.38	0.14	0.02	0.03	0.43	0.01
	5	0.20	0.25	0.07	0.15	0.29	0.03
	20	0.20	0.24	0.10	0.16	0.22	0.08

The relevance of financial shocks can also be deduced from the impulse responses plotted in Figure 1. We remark a large and hump-shaped effect on output but a limited impact on prices. The response of investment and stock prices is persistent although we impose our restrictions only on impact. Furthermore, despite being unrestricted in the estimation, the response of the spread is strongly countercyclical, thus validating our estimated financial shock.

Figure 2 shows the historical decomposition in which we display the contribution of each structural shock to the total forecast error at each point in time. Financial shocks play a large role in driving down output during the Great Recession as well as in more recent years. However, financial shocks are also active in boom periods like the entire decade going from the beginning of the 1990s until the beginning of the 2000s (together with positive supply shocks) and around the mid 2000s (together with positive supply, demand and monetary policy shocks).

The limited response of prices to financial shocks is an important result of this paper that has not been discussed in the previous literature. It can be used to interpret why inflation was surprisingly low during stock market and credit booms in the US (cf. Christiano *et al.*, 2010) and why inflation was surprisingly high in the aftermath of the Great Recession despite the size of the contraction in output and employment.[10] Our model describes the three stock market booms included in our sample (1985-1987, 1994-2000, 2003-2007) as periods characterised by positive supply and financial shocks. Along the same lines, the Great Recession is a period of large negative supply and financial shocks, so that a large output drop coexists with a limited decrease in inflation. In the post-Great Recession period, the relative importance of financial shocks accounts for the limited adjustment in inflation.

While the focus of this paper is on the effects of financial shocks, it is nevertheless interesting to comment on the model's predictions for the other identified shocks. Figure 3 presents the median impulse responses for each variable. The supply shock generates large effects on output but also on investment and stock prices. These effects are consistent with the dynamics induced by a standard technology shock in DSGE models.[11] Monetary shocks have a protracted positive effect on output. Nonetheless, according to our model their macroeconomic relevance seems to be limited and we do not find any systematic effect on the stock market. In keeping with Christiano *et al.* (2014), the inclusion of financial variables in the model crowds out the investment shock, which maintains limited explanatory power. In addition, the choice of a post-Great Moderation sample period may also rationalise this result. Demand shocks have small effects on output, investment and the stock market but are the main driver of prices. Finally, our model provides useful information on the conditional response of the spread to shocks:

[10]Christiano *et al.*, 2010) document that inflation was relatively low in each of the 18 stock market boom episodes that have occurred in the past two centuries in the US. The same is true for the Japanese stock market boom of the 1980s.

[11]However, it is important to recognise that the supply shock captures also the dynamics induced by any other shock that may drive output and prices in different directions. This is the case for price mark-up shocks and for shocks originating in the labour market, such as labour supply, wage mark-up and matching efficiency shocks.

it is countercyclical in response to demand, investment and supply shocks, and procyclical in response to monetary policy shocks. Figure 4 shows that financial shocks are the most important drivers of the spread but not the exclusive ones. This result is consistent with the variance decomposition where the spread appears as a fully endogenous variable that responds to all shocks in the system. Moreover, the presence of some negative supply shocks rationalise the "missing deflation" in recent years.

Table 3: *Fraction of Variance Explained by Financial Shocks in the Forecast Error of GDP under Alternative Specifications and Measures of Central Tendency*

Horizon	Pre-2008	Fry-Pagan	Modal Model	2 lags
1	0.14	0.34	0.57	0.26
5	0.17	0.33	0.62	0.30
20	0.21	0.37	0.48	0.30

We now present a short summary of the sensitivity analysis presented in the Online Appendix (Section B) by focusing on the relative importance of financial shocks (cf. Table 3). In a first experiment we reduce the sample period by re-estimating the model with data until 2007-Q2 to evaluate the influence of the Great Recession on our results. In a second set of experiments we consider two alternative measures of central tendency such as the median target proposed by Fry and Pagan (2011) and the modal model proposed by Inoue and Kilian (2013). Finally, we re-estimate the model with two lags, i.e. the number of lags suggested by both the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC). Not surprisingly, financial shocks are somewhat less important when we exclude the Great Recession from the sample. In contrast, their role is strengthened when we use the median target measure of central tendency and when we use only two lags in the estimation. In keeping with Inoue and Kilian (2013), results change substantially when we consider the modal model measure of central tendency: in this case financial shocks become even dominant.

3 Disentangling Financial Shocks

In the previous section we identified a general financial shock and showed that i) it is important for output fluctuations, ii) it has limited impact on inflation, and iii) it is empirically plausible since it generates a countercyclical premium. In this section we disentangle the financial shock into different components. In particular, we evaluate shocks originating in the housing sector, in credit markets and uncertainty shocks. To the best of our knowledge, DSGE models do not provide robust restrictions to differentiate these shocks on the basis of the sign of impulse-responses. Therefore, we rely on assumptions about the magnitude of the responses.

Since we increase the number of identified financial shocks, we need to sacrifice two of the non-financial shocks for computational reasons. A natural candidate is the residual shock that plays a minor role into the system. In addition, we remove the monetary policy shock too. In fact, as shown by Paustian (2007), Canova and Paustian (2011) and Castelnuovo (2013), sign restrictions are accurate only when the identified shocks are sufficiently large. Monetary policy shocks are typically found to be of limited quantitative importance for US business cycle fluctuations. Moreover, interest rate dynamics largely mimic inflation dynamics in our VAR, thus suggesting that other macroeconomic series may be more informative to describe the business cycle.

3.1 Housing Shocks and Credit Shocks

In our main extension we aim at disentangling shocks originating in the housing sector from shocks originating in credit markets. These shocks may have a broad economic interpretation and capture housing preference shocks or bubbles in real estate markets on the housing side, and credit market liberalizations or relaxations in credit standards on the credit side. They also have a (narrower) empirical counterpart in the macroeconomic literature. An example of a shock originating in the housing sector is the housing demand shock introduced by Iacoviello and Neri (2010), whereas an example of a shock originating in the credit markets is the shock to the loan-to-value ratio in models with collateral constraints (cf. Justiniano *et al.*, 2015, and Liu *et al.*, 2013). While both shocks generate an increase in investment and in stock prices in response to an expansionary impulse (in keeping with our definition of a financial shock), the macroeconomic literature does not provide a robust sign restriction to distinguish the two shocks.[12]

Table 4: *Restrictions in the Extended Model with Credit and Housing Shocks*

	Supply	Demand	Investment	Housing	Credit
GDP	+	+	+	+	+
Prices	-	+	+	+	+
Investment/Output	NA	-	+	+	+
Stock Prices	NA	NA	-	+	+
Credit/Real Estate Value	NA	NA	NA	-	+

The Table describes the restrictions used for each variable or ratio (in rows) to identified shocks (in columns) in our VAR. NA indicates that the response of the variable is left unrestricted.

We disentangle the two shocks by imposing a restriction on the magnitude of the response of credit and house prices that we implement through a sign restriction on the response of the credit-to-real-estate-value ratio, as detailed in Table 4. This ratio relates a measure of total credit to households and firms to the total value of the housing stock as reported by the Flow of Funds tables. In addition to the sign restrictions that we have used to identify our general financial shock in Section 1, we assume that an expansionary credit shock has a positive effect on the ratio whereas an expansionary housing shock lowers the ratio. Suppose a positive credit shock such as an expansionary loan-to-value shock. The shock generates an increase in credit and may generate an increase in house prices. The only restriction that we impose is that the increase in the housing value on impact (and only on impact) has to be lower than the increase

[12]The housing demand shock was studied first by Iacoviello and Neri (2010). In that model a positive shock increases residential investment but crowds out business investment, thus invalidating our identifying assumption on aggregate investment. However, Walentin (2014a) shows that the use of investment adjustment costs, rather than capital adjustment costs as in Iacoviello and Neri (2010), favours a positive response of business investment. Furthermore, Liu *et al.* (2013) document that land prices and business investment strongly correlate over the business cycle and provide a model with collateral constraints on the firm side that reproduce a positive comovement between business investment and residential investment in response to a housing demand shock.

in credit. This is in keeping with a large literature summarised in Justiniano *et al.* (2015) showing that shocks to the loan-to-value ratio have limited effects on house price dynamics. Consider now an increase in house prices (perhaps induced by a housing preference shock). Our restriction allows credit to increase on the impact of the shock, but its increase has to be lower than the one in the housing value. While an increase in collateral values driven by a housing boom certainly calls for an expansion in credit, we assume that this endogenous relaxation of lending standards has to be limited on impact of the shock. We believe that it is a reasonable assumption in normal times, although it is possible that in some specific episodes the endogenous relaxation in lending standards may have been large.

Table 5: *Median Forecast Error Variance Decompositions for the Model Including Housing and Credit shocks*

	Horizon	Supply	Demand	Investment	Credit	Housing
GDP	1	0.58	0.05	0.09	0.15	0.13
	5	0.66	0.02	0.02	0.05	0.24
	20	0.44	0.01	0.07	0.05	0.44
Prices	1	0.64	0.09	0.12	0.07	0.08
	5	0.13	0.42	0.09	0.10	0.27
	20	0.22	0.42	0.08	0.06	0.22
Investment	1	0.24	0.04	0.29	0.19	0.23
	5	0.51	0.01	0.04	0.07	0.37
	20	0.26	0.02	0.07	0.13	0.53
Stock Prices	1	0.16	0.00	0.41	0.18	0.24
	5	0.26	0.01	0.29	0.10	0.34
	20	0.19	0.01	0.14	0.05	0.62
Credit/ Real Estate Value	1	0.01	0.00	0.00	0.23	0.75
	5	0.04	0.00	0.00	0.55	0.41
	20	0.03	0.00	0.03	0.56	0.37

The variance decomposition in Table 5 documents that the explanatory power of financial shocks is now largely absorbed by housing shocks. While the contribution of credit shocks is not negligible, the importance of housing shocks is substantially larger and the sum of the two shocks confirms the results described for the general financial shock identified in Section 2 (although housing shocks now have a somewhat larger effect on inflation). From impulse responses in Figures 5 and 6 we see that the restriction on the credit-to-real-estate-value ratio, despite being imposed only on impact, is satisfied over several quarters for both shocks. The effects of housing shocks are large and very persistent, whereas the impact of credit shocks is short-lived.

At this stage it is important to stress that our housing shock may have several interpretations. So far we have emphasised the link with housing demand shocks but other stories can be consistent with the dynamics induced by our housing shock, like bubbles in the real estate sector or changes in households beliefs on house prices as discussed in Lambertini *et al.* (2013) and Pancrazi and Pietrunti (2014). Alternative interpretations involve productivity dynamics in the construction sector or international factors. Iacoviello and Neri (2010) and Galesi (2014) document that the housing boom has been associated to a slowdown in relative productivity in construction. External factors, such as the global saving glut discussed in an influential speech by then Fed Governor Ben Bernanke (2005), may also be captured by our housing shock. Whatever the more appropriate interpretation, it is evident from our identification strategy that a good business cycle shock is a shock that moves output and credit-to-real-estate-value ratio in opposite directions.

In Table 6 we propose a summary of the sensitivity analysis that is performed in the Online Appendix (Section C). In addition to the four experiments considered in the baseline model, we propose here two additional exercises. In the first case we focus on household credit (rather than total credit) and we re-estimate the model by using data on the mortgages-to-real-estate-value ratio: the role of the two financial shocks is somewhat reduced in this case. In the second experiment we want to reconsider our identifying assumption on the credit-to-real-estate-value ratio. In fact, while both credit and the real estate value are stock variables, credit is more slow moving since most loan contracts are long-term and only a share is refinanced every quarter. Therefore, we may be worried whether the stock of credit effectively reacts more than the real estate value on the impact of a shock originating in the credit markets. To address this possible criticism, we impose the restriction on the ratio of credit in first differences (rather than in levels) to the real estate value. Credit in first differences captures only the new loans accorded in the period, once the separation margin is taken into account (i.e. the fact that some loans are not renewed). Therefore, we now have a flow variable in the numerator of our ratio that potentially can react significantly on the impact of the shock. Credit shocks become now slightly more important but the role of the housing shock is preserved, in particular in the long-run.

Table 6: *Fraction of Variance Explained by Credit and Housing Shocks in the Forecast Error of GDP under Alternative Specifications and Measures of Central Tendency*

	Horizon	Pre-2008	Fry-Pagan	Modal Model	2 lags	Mortgages	New Credit
Credit							
	1	0.16	0.28	0.19	0.16	0.11	0.16
	5	0.14	0.16	0.11	0.05	0.05	0.23
	20	0.12	0.07	0.03	0.01	0.12	0.19
Housing							
	1	0.13	0.23	0.25	0.18	0.11	0.12
	5	0.21	0.18	0.35	0.39	0.15	0.17
	20	0.13	0.54	0.58	0.57	0.16	0.34

3.2 Additional Extensions: Uncertainty and Credit Supply Shocks

The goal of this section is to further disentangle the financial shock into different components. In a first experiment we consider uncertainty shocks. Bloom (2009) finds that contractionary uncertainty shocks induce a drop in investment that is followed by a rebound and even an overshoot of the initial values. Interestingly, a negative credit shock induces this kind of dynamics for investment in our estimated VAR (cf. Figure 5). This observation let us conjecture that our identified credit shock may be contaminated by the presence of uncertainty shocks. To disentangle credit and uncertainty shocks, we use data on the excess bond premium (EBP) measure constructed by Gilchrist and Zakrajsek (2012) and a measure of stock market volatility, VIX, to identify the shocks. We impose sign restrictions on the ratio of these financial variables. While we assume that expansionary credit and uncertainty shocks both lower the EBP on impact, to achieve identification we assume that the adjusted ratio of EBP/VIX decreases in response to a positive uncertainty shock, whereas it increases in response to a shock originating in the credit markets. The two variables are introduced separately into the reduced form model but the restrictions are implemented on the ratio of the two variables (and on the EBP itself).[13] Implicitly, we are thus assuming that the VIX reacts more to uncertainty shocks and that the EBP reacts more to credit shocks. While the sign of the responses may very well be the same across the two shocks, we rely on restrictions on the magnitude of the responses to achieve identification. One advantage of this identification procedure is that the order of the variables does not matter for identification purposes. Importantly, in our set-up uncertainty shocks and credit shocks are estimated together with the other shocks discussed in the previous section and all the restrictions are summarised in Table 7.

Table 7: *Restrictions in the Extended Model with Credit, Housing and Uncertainty shocks*

	Supply	Demand	Investment	Housing	Credit	Uncertainty
GDP	+	+	+	+	+	+
Prices	-	+	+	+	+	+
Investment/Output	NA	-	+	+	+	+
Stock Prices	+	NA	-	+	+	+
Credit/Real Estate Value	NA	NA	NA	-	+	+
EBP	NA	NA	NA	NA	-	-
EBP/VIX	NA	NA	NA	NA	-	+

The table describes the restrictions used for each variable or ratio (in rows) to identified shocks (in columns) in our VAR. NA indicates that the response of the variable is left unrestricted.

We report the variance decomposition in Table 8. The key role of shocks originating in the housing sector is confirmed in this extended version of the model, above all at medium and long horizons. In the short-run both credit and uncertainty shocks play a role, so that the sum

[13]In contrast to the other ratios used in this paper, the numerator and the denominator of the EBP/VIX ratio are measured in different units. Hence, to impose meaningful sign restrictions on the responses of the EBP/VIX ratio, we have adjusted the EBP series such that its first two moments are equivalent to the first two moments of the VIX series. Notice that the system includes seven variables in this experiment since both EBP and VIX are introduced separately in the reduced form VAR. As in the baseline model described in Section 1, one residual shock is included to match the number of variables and shocks.

Table 8: *Median Forecast Error Variance Decompositions for the Model Including Housing, Credit and Uncertainty Shocks*

	Horizon	Supply	Demand	Investment	Housing	Credit	Uncertainty	Residual
GDP	1	0.39	0.05	0.10	0.16	0.15	0.15	0.00
	5	0.39	0.04	0.04	0.27	0.19	0.06	0.00
	20	0.08	0.01	0.17	0.59	0.07	0.07	0.01
Prices	1	0.56	0.09	0.15	0.09	0.04	0.06	0.00
	5	0.14	0.44	0.14	0.14	0.05	0.09	0.01
	20	0.06	0.42	0.14	0.27	0.04	0.05	0.02
Investment	1	0.13	0.03	0.26	0.21	0.20	0.13	0.03
	5	0.24	0.02	0.07	0.40	0.16	0.10	0.01
	20	0.07	0.02	0.17	0.58	0.04	0.12	0.01
Stock Prices	1	0.10	0.00	0.45	0.16	0.13	0.13	0.02
	5	0.06	0.01	0.29	0.40	0.15	0.08	0.01
	20	0.07	0.00	0.17	0.56	0.14	0.04	0.01
Credit / Real Estate	1	0.01	0.00	0.00	0.74	0.08	0.17	0.00
	5	0.01	0.00	0.01	0.47	0.25	0.25	0.00
	20	0.01	0.01	0.08	0.48	0.16	0.26	0.00
EBP	1	0.00	0.13	0.01	0.35	0.44	0.07	0.00
	5	0.04	0.12	0.04	0.38	0.19	0.21	0.01
	20	0.08	0.08	0.15	0.32	0.16	0.19	0.01
VIX	1	0.02	0.01	0.14	0.07	0.16	0.60	0.00
	5	0.01	0.05	0.22	0.11	0.25	0.35	0.01
	20	0.03	0.04	0.23	0.17	0.24	0.27	0.01

of the three financial shocks explain on average around 50% of fluctuations in output. Such an important role for the three financial shocks is remarkable in a quarterly model since one may expect that part of the relevant variation in financial variables and uncertainty proxies gets diluted once lower frequencies are at play. The non-inflationary effect of financial shocks highlighted in Section 2 is also present here, at least for short horizons.

Let us now turn to the analysis of credit and uncertainty shocks, which constitutes the key insight of this experiment (cf. Figure 7 for selected impulse responses). Credit shocks have now a more persistent effect on the macroeconomic variables and are a non-negligible driver of GDP, investment and stock prices. Positive uncertainty shocks (reduced uncertainty) boost output, investment and stock prices, but only in the short run. The effects quickly become not significant (the median impulse response even turns negative after 4 quarters) driven by an increase in VIX that, after a large drop on impact, starts increasing after three quarters, thus depressing economic activity. While the effects of housing shocks (and to some extent of credit shocks) are persistent, the effects of uncertainty shocks are short-lived and of limited importance for macroeconomic dynamics. Notably, the investment response to uncertainty shocks closely match the drop, rebound and overshoot behavior described in Bloom (2009).[14]

Table 9: *Restrictions in the Extended Model with Credit Demand and Supply Shocks*

	Supply	Demand	Investment	Housing	Credit Supply	Credit Demand
GDP	+	+	+	+	+	+
Prices	-	+	+	+	+	+
Investment/Output	NA	-	+	+	+	+
Stock Prices	NA	NA	-	+	+	+
Credit/Real Estate Value	NA	NA	NA	-	+	+
Mortgage Rates	NA	NA	NA	NA	-	+

The table describes the restrictions used for each variable or ratio (in rows) to identified shocks (in columns) in our VAR. NA indicates that the response of the variable is left unrestricted.

We now consider a second extension whose goal is to further disentangle the shock originating in the credit markets into two components by using data on mortgage interest rates taken from the Federal Housing Finance Board and available from 1990:Q1. The sample period is adjusted accordingly. We identify a credit demand shock that moves output and the mortgage interest rate in the same direction and a credit supply shock that moves output and the mortgage interest rate in opposite directions. The former may capture relaxations in collateral constraints, perhaps driven by variations in loan-to-value ratio requirements (cf. Duca, Muellbauer and Murphy, 2011, among others). The latter may capture relaxations in leverage restrictions for financial intermediaries, perhaps favoured by the explosion of securitization and of market-based financial intermediation (cf. Peersman and Wagner, 2015, and Justiniano *et*

[14]A cautionary note on the structural interpretation of the drop-rebound-and-overshoot dynamics is warranted here. The investment impulse response exhibits the same patterns in response to other shocks (cf. Figure 3) and not only to uncertainty shocks. Therefore, we cannot rule out that these kinds of dynamics simply reflect the structure of the reduced form model that features complex eigenvalues in the companion matrix inducing the cycling behavior in some impulse responses. Notably, these dynamics do not characterise the investment response to housing and supply shocks that are the most important shocks in our set-up.

al., 2016). We maintain the assumption that the credit to real estate value is procyclical in response to both credit shocks. The restrictions imposed in this last experiment are summarised in Table 9.

In Figure 8 we plot the impulse-responses of output and mortgage rates to the three financial shocks. We remark that only housing and credit supply shocks generate large expansionary effects on output. Credit demand shocks have a sizeable effect on the mortgage interest rate but small and short-lived effects on GDP. Notice that expansionary housing shocks generate an increase in the mortgage interest rate. This a genuine feature driven by the data since the variable is left unrestricted in the system in response to housing shocks. According to the variance decomposition in Table 10, the three financial shocks grouped together are the dominant source of fluctuations together with supply shocks as in previous experiments.

Table 10: *Median Forecast Error Variance Decompositions for the Model Including Housing, Credit Demand and Credit Supply Shocks*

	Horizon	Supply	Demand	Investment	Housing	Credit Supply	Credit Demand
GDP	1	0.58	0.03	0.05	0.11	0.07	0.16
	5	0.68	0.01	0.03	0.13	0.09	0.05
	20	0.35	0.08	0.08	0.05	0.17	0.26
Prices	1	0.71	0.10	0.08	0.04	0.04	0.03
	5	0.15	0.42	0.02	0.24	0.07	0.11
	20	0.08	0.31	0.08	0.13	0.06	0.34
Investment	1	0.23	0.06	0.29	0.18	0.12	0.13
	5	0.52	0.01	0.07	0.21	0.11	0.07
	20	0.18	0.12	0.14	0.08	0.14	0.33
Stock Prices	1	0.34	0.02	0.26	0.17	0.10	0.10
	5	0.56	0.01	0.18	0.12	0.06	0.06
	20	0.37	0.12	0.14	0.10	0.16	0.11
Credit / Real Estate	1	0.00	0.05	0.01	0.67	0.08	0.19
	5	0.02	0.03	0.09	0.15	0.05	0.66
	20	0.03	0.10	0.16	0.06	0.04	0.60
Mortgage Rates	1	0.00	0.00	0.02	0.05	0.16	0.76
	5	0.02	0.06	0.04	0.06	0.10	0.70
	20	0.07	0.05	0.08	0.06	0.10	0.64

The credit demand shock is relatively important in the long run but this result is entirely driven by the extreme drop, rebound and overshoot dynamics that may be driven by uncertainty shocks as shown in the previous experiment. Housing shocks maintain an important role for business cycle dynamics, although a substantial fraction of their explanatory power in the long run is now absorbed by credit supply shocks. We conclude that the use of data on mortgage interest rates, that exhibits a steep decline in the beginning of the 2000s (cf. Justiniano *et al.*, 2016), favour a meaningful role for credit supply factors. Nevertheless, the dynamics in the credit-to-real-estate-value series contribute to preserve a role for housing shocks. Despite generating pro-cyclical mortgage rates, housing shocks explain a rather large share of output fluctuations during the pre-Great Recession boom and the subsequent bust (cf. the historical decomposition presented in the Online Appendix, Section D). We conclude that the decline of mortgage rates over the first half of the 2000s is not sufficient to rule out a role for shocks originating in the housing sector in driving the pre-Great Recession boom.

4 Implications for Macroeconomic Models

In the previous sections we have proposed a large set of results derived from a series of VAR models constrained only by a minimum set of identification assumptions. The VAR approach is often seen as a useful comparison (and sometimes also as a validation check) for fully specified macroeconomic models that impose substantial structure on the data in the form of tight cross-equation restrictions. The objective of this section is to highlight the results that may be more relevant to evaluate macroeconomic models with financial shocks.

Business cycle and inflation dynamics. In our baseline estimated model financial shocks are important for business cycle fluctuations but play a minor role for inflation dynamics, thus confirming in a VAR set-up the main results emerging from the seminal paper by Christiano *et al.* (2014).[15] Importantly, however, a news component is necessary for the financial shock

[15] In the Online Appendix (Section E) we replicate in a VAR set-up the exercise with two financial shocks

to be the main driver of business cycle fluctuations in the Christiano *et al.* (2014) model. In our VAR unanticipated shocks are important on their own.

Drivers of the external finance premium and the VIX. Financial shocks are important drivers of the external financial premium in our baseline VAR model. However, the other shocks (and supply shocks in particular) also play a substantial role. This is in contrast with state of the art DSGE models (cf. Christiano *et al.*, 2014; Ajello, 2016) where the premium is driven almost exclusively by financial shocks. Along the same lines, our extension with uncertainty shocks shows that at least 40% of VIX fluctuations at short horizon and at least 70% at long horizon are driven by shocks other than uncertainty. This result challenges the traditional practice in the literature of considering volatility measures as exogenous. We highlight an important endogenous component driven by other financial and macro shocks.

Cyclicality of the external finance premium. While all DSGE models we are aware of generate a countercyclical premium in response to a financial shock, there is considerable more uncertainty on the conditional response of the premium to other macroeconomic shocks. In fact, the response of the premium to shocks depends on how the capital accumulation process and the financial frictions are modeled. Walentin (2005) shows that the premium is countercyclical to all shocks in the standard financial accelerator model with capital adjustment costs and a debt contract specified in terms of the real interest rate, as in Bernanke, Gertler and Gilchrist (1999). De Graeve (2008) changes the specification of the capital accumulation process by using investment adjustment costs rather than capital adjustment costs in an estimated model for the US. With investment adjustment costs, the premium becomes procyclical in response to investment and demand (preference) shocks and weakly countercyclical in response to technology shocks, but it remains countercyclical in response to monetary shocks. Gelain (2010) finds similar results on European data. Christensen and Dib (2008) change the form

considered by Christiano *et al.* (2014) in their model with a financial accelerator. Following the structure of the theoretical model, we assume that a net worth shock moves output and credit in opposite directions whereas a risk shock moves them in the same direction. Risk shocks explain the bulk of fluctuations due to financial shocks, thus confirming the main result in Christiano *et al.* (2014).

of the debt contract and specify it in terms of the nominal (rather than real) interest rate, thus allowing for debt-deflation effects. In that context the premium becomes procyclical in response to technology, demand (preference) and investment shocks but remains countercyclical to monetary shocks. According to our analysis, all these results are counterfactual. As far as we know, the only model that matches our empirical evidence is the financial accelerator model with a debt contract indexed to aggregate conditions, as in Carlstrom *et al.* (2014). That model generates a procyclical premium in response to a monetary policy shock and is consistent with our evidence also for investment and financial shocks.

Stock market response to monetary policy. In our baseline estimated model the stock market is largely driven by financial shocks and does not respond to monetary policy shocks. This is interesting in light of the debate opened by Gali' and Gambetti (2015) who challenge the "conventional wisdom" that expansionary monetary policy shocks should have a positive effect on the stock market and show that a negative response may be expected in the presence of a bubble component. Our results support Gali' and Gambetti (2015) insofar as monetary shocks are not effective at curbing stock market dynamics.

Housing shocks. Our result on the importance of shocks originating in the housing sector is obtained using data on total credit to the non-financial sector which includes both households and firms. Liu *et al.* (2013) find a similar result in a DSGE model with collateral constraints on the firm side that uses data on credit to the corporate sector. In that model the two financial shocks (housing and credit) account for about 30% of the fluctuations in output with the housing shock alone explaining more than 20% of output fluctuations. Justiniano *et al.* (2015) also find that credit shocks alone cannot explain the leveraging and deleveraging cycle that the US has experienced in the last 20 years in a calibrated non-linear model which focuses on household credit. They argue that housing demand shocks are more promising to explain the evolution of debt and leverage, although in their non-linear model both financial shocks have limited effects on output.

5 Conclusion

The objective of this paper is to evaluate the importance of shocks originating in the financial sector to explain business cycle fluctuations in a sign-restricted VAR. In a first step we consider a general financial shock whose defining features are borrowed from the recent literature on DSGE models with financial frictions. We find that financial shocks are important for output fluctuations but play a limited role in explaining inflation dynamics. In an extended set-up we consider several financial shocks (housing, credit and uncertainty shocks) identified more on the basis of the magnitude of the responses rather than on the sign of the responses. In this extended set-up financial shocks are even more important and a leading, although non exclusive, role is played by shocks originating in the housing market. This result echoes the finding in Leamer (2007) that "Housing is the business cycle".

We identify two avenues for future research. First, it would be interesting to better understand the nature of housing shocks, i.e. shocks that move output and the credit-to-real-estate-value ratio in opposite directions. The policy implications may be radically different depending on whether they represent efficient preference shocks or a productivity slowdown in the construction sector (as in Iacoviello and Neri, 2010), whether they capture inefficiencies like bubbles or whether they absorb other disturbances that we have not isolated in our analysis (as open economy factors, for example). Second, it seems important to scrutinise further the link between financial factors and inflation. In most of our estimated VAR models, despite imposing that inflation should increase in response to a positive financial shock, we find that this response is limited. While most financial shocks are inflationary in theoretical models, some financial shocks may have deflationary effects. Extending our framework to study deflationary financial shocks seems an interesting idea for future research.

Finally, let us stress that we concentrated our attention only on the US case. Our results do not necessarily carry over to other countries that are potentially different in terms of mortgage markets, financial regulation and structure of the banking sector. It would be interesting to apply our baseline identification scheme to other countries, in particular small open economies and countries that did not experience the housing boom.

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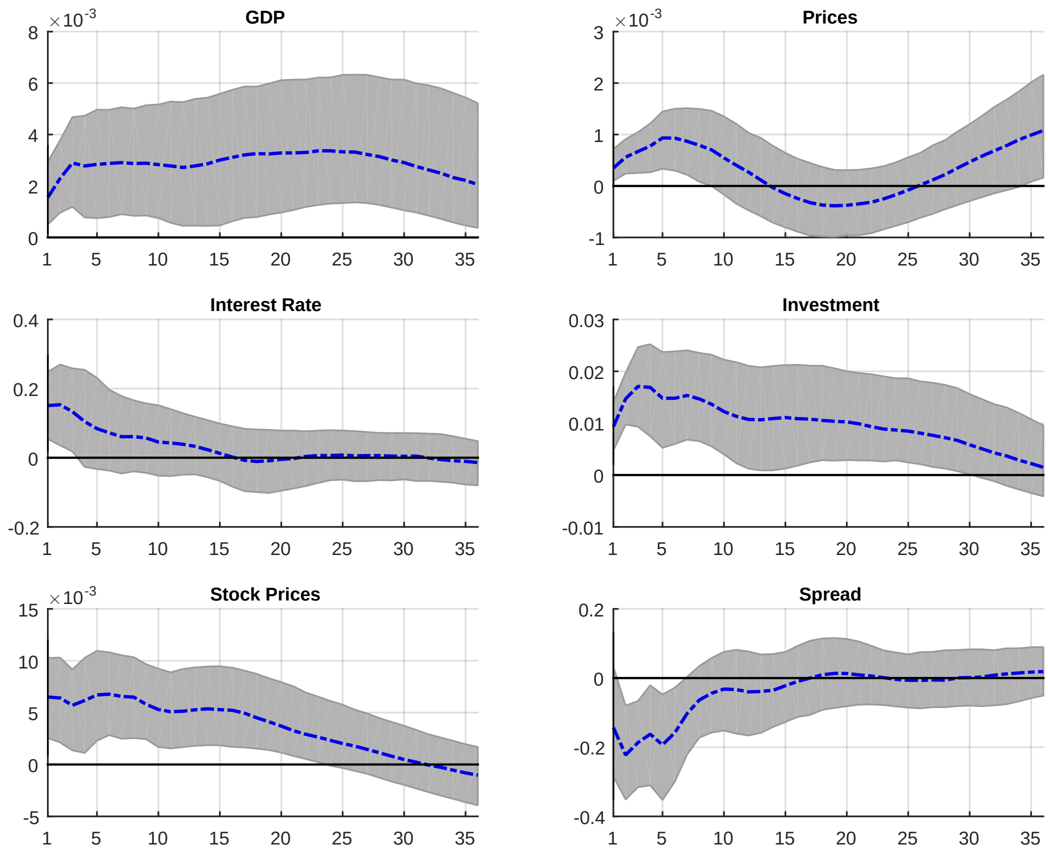
Table 11: *Data and Sources*

Variable	Description	Source
GDP	Log of Real GNP/GDP	Federal Reserve Bank of Philadelphia
GDP Deflator	Log of Price Index for GNP/GDP	Federal Reserve Bank of Philadelphia
Interest Rate	3-Month Treasury Bill	Federal Reserve Bank of St. Louis
Investment	Log of Real Gross Private Domestic Investment	Federal Reserve Bank of St. Louis
Stock Prices	Log of S&P 500	Yahoo Finance
Total Credit	Log of Loans to Non-Financial Private Sector	Board of Governors of the Federal Reserve System
Mortgages	Log of Home Mortgages of Households and Nonprofit Organizations	Board of Governors of the Federal Reserve System
Real Estate Value	Log of Real Estate at Market Value of Households and Nonprofit organizations	Board of Governors of the Federal Reserve System
Corporate Bond Yield	Moody's Baa Corporate Bond Yield	Federal Reserve Bank of St. Louis
10y Treasure Note	10-Year Treasury Const. Mat. Rate	Federal Reserve Bank of St. Louis
Federal Funds Rate	Federal Funds Rate	Federal Reserve Bank of St. Louis
GZ credit spread	Senior Unsecured Corporate Bond Spreads (Nonfinancial Firms)	Gilchrist and Zakrajsek (2012)
EBP	Excess Bond Premium	Gilchrist and Zakrajsek (2012)
VIX	Stock Market Volatility Index	Bloom (2009)
Mortgage Rates	Home Mortgages, Fixed 30YR, Effective Interest Rate	Federal Housing Finance Board

GDP series is real GNP prior to 1991 and real GDP from 1991 onwards.

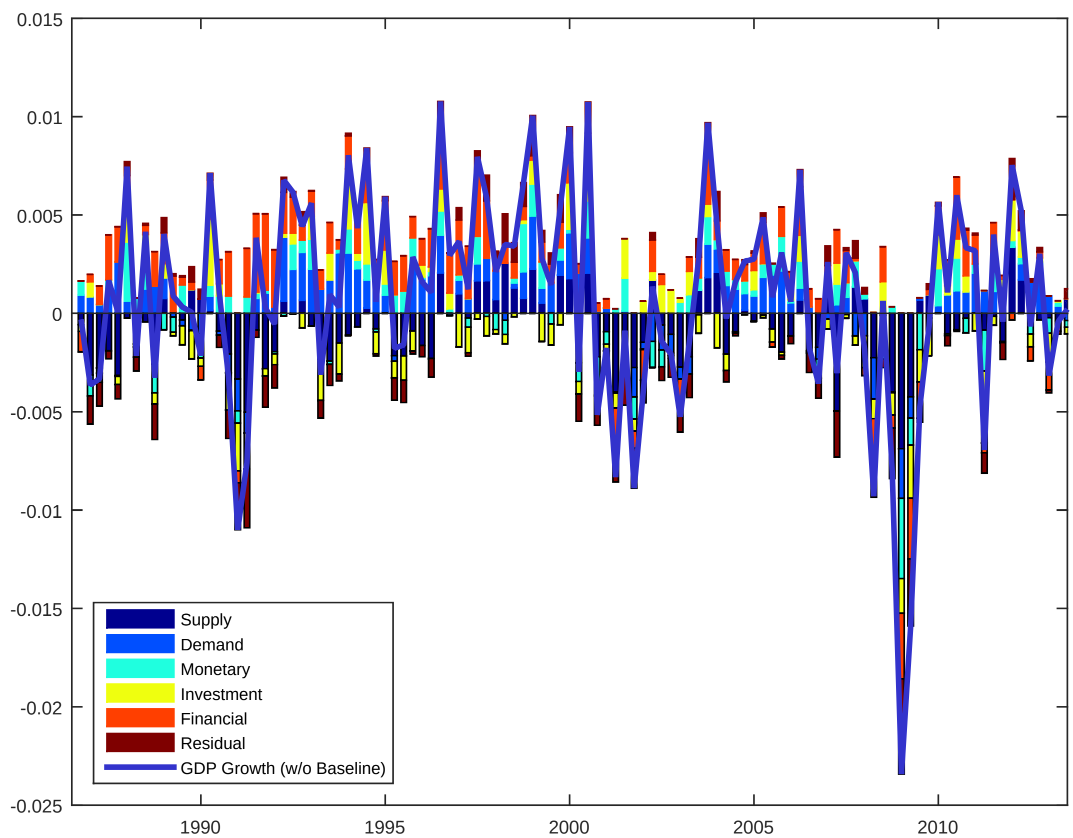
S&P 500 series is deflated with the price index for GNP/GDP.

Figure 1: *Impulse Responses for the Baseline Model to an One-Standard-Deviation Financial Shock*



The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

Figure 2: *Contribution of Shocks to Deviations in GDP Growth from its Baseline Forecast for the Period 1985-2013*



The historical decomposition is calculated by first transforming the series of reduced form residuals to a series of structural residuals and then computing the cumulative contributions of each structural component to the reduced form forecast error.

Figure 3: *Median Impulse Responses for the Baseline Model to an One-Standard-Deviation Supply, Demand, Monetary, and Investment Shock*

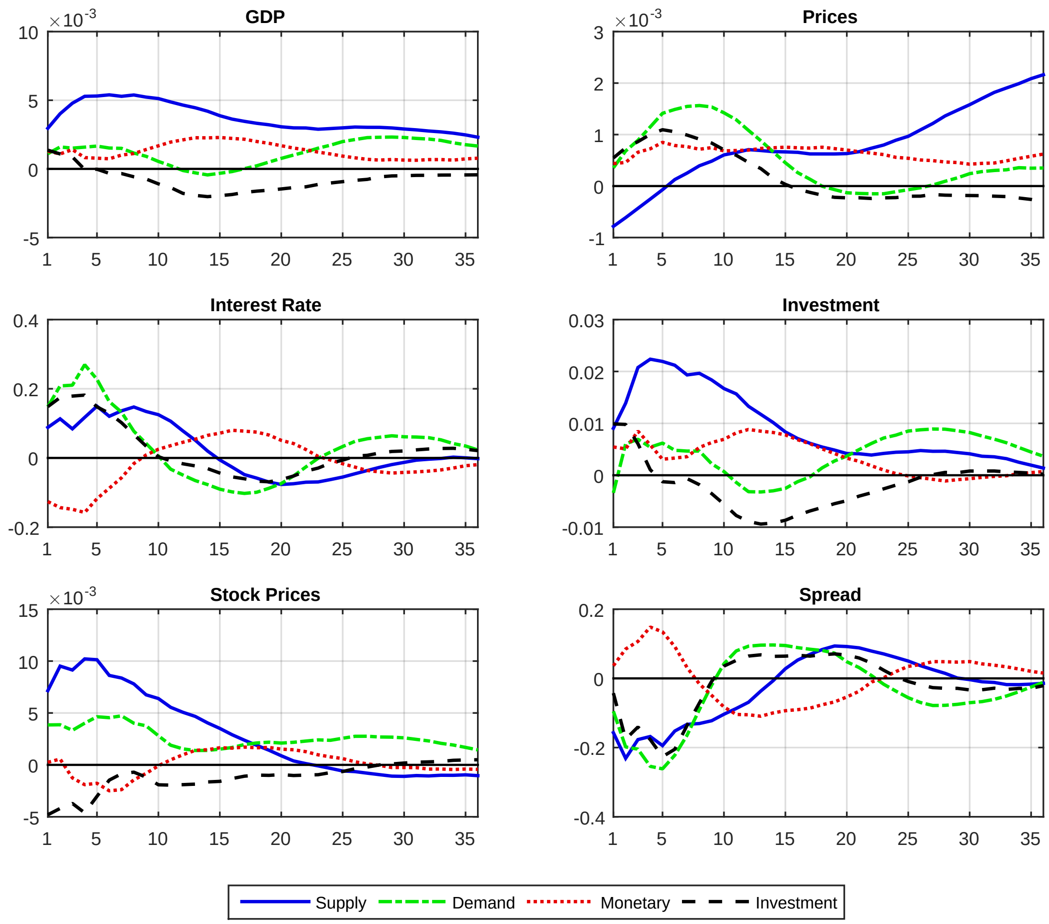
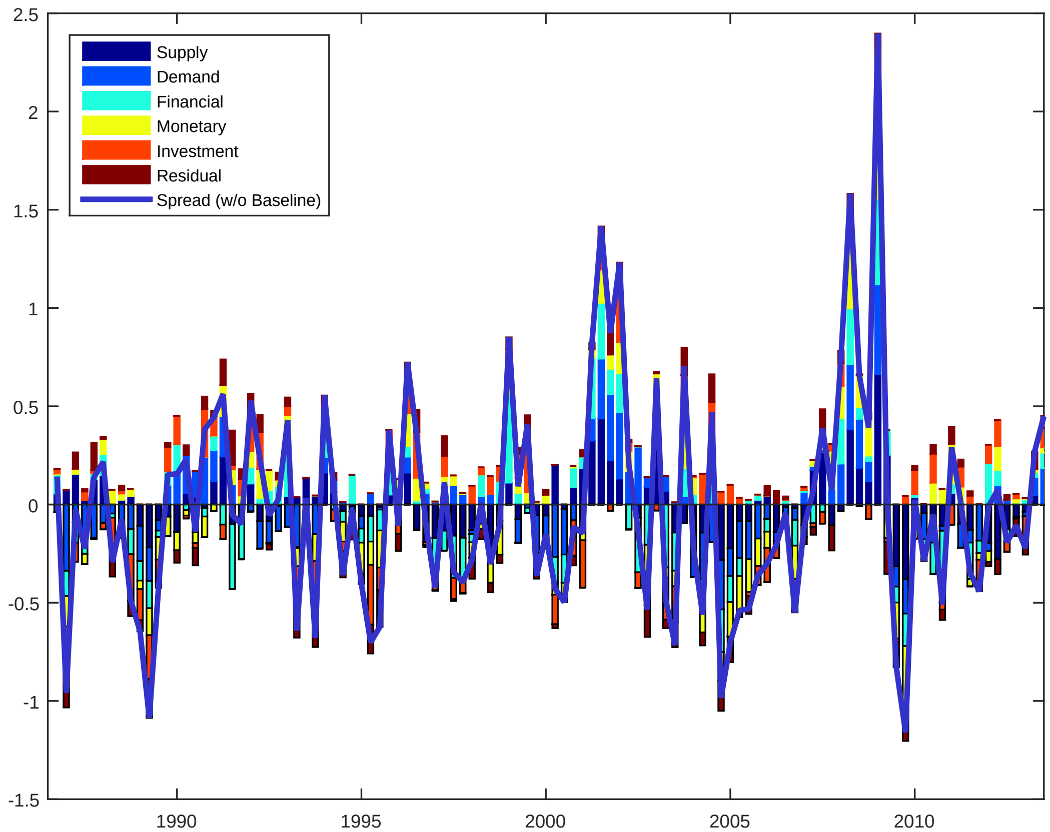
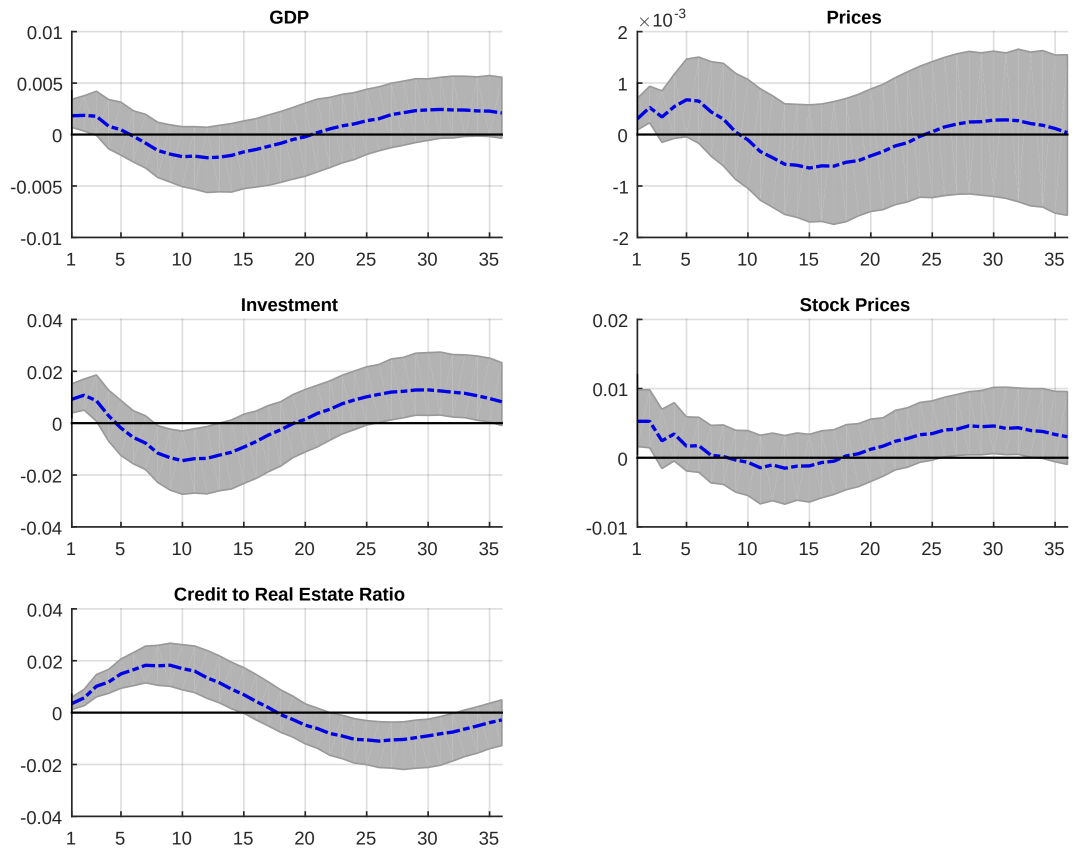


Figure 4: *Contribution of Shocks to Deviations in the Spread Measure from its Baseline Forecast for the Period 1985-2013*



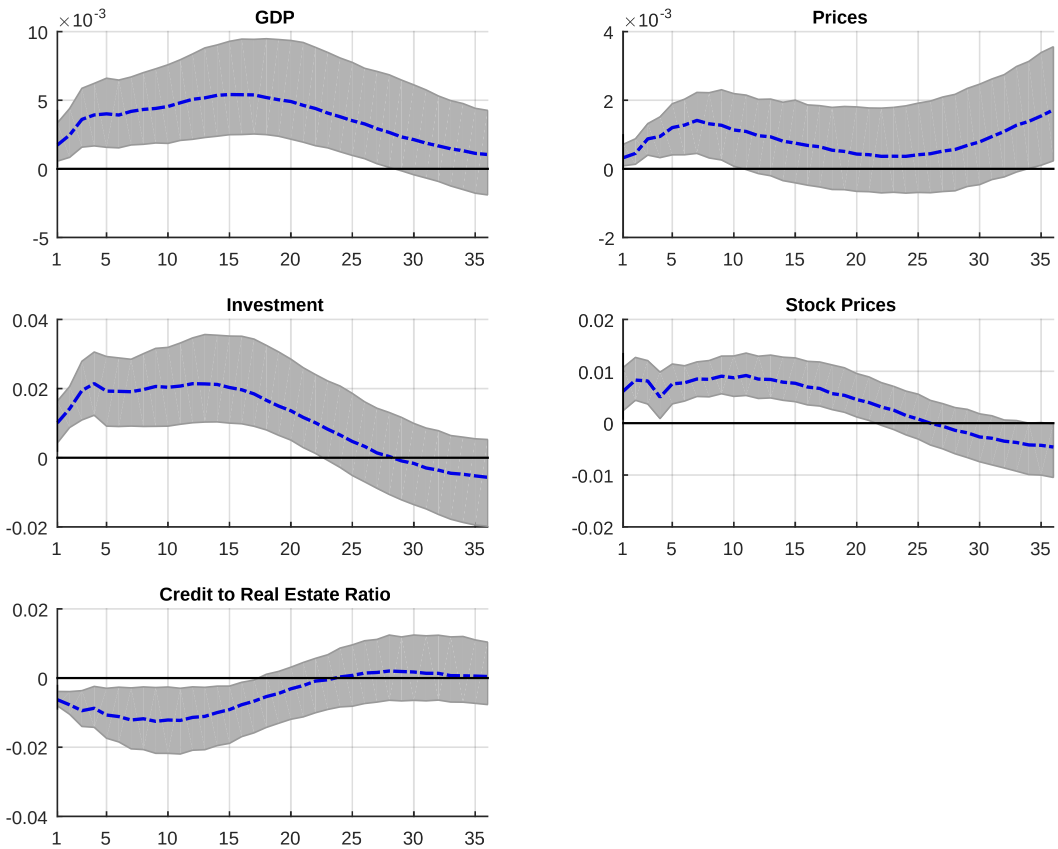
The historical decomposition is calculated by first transforming the series of reduced form residuals to a series of structural residuals and then computing the cumulative contributions of each structural component to the reduced form forecast error.

Figure 5: *Impulse Responses to an One-Standard-Deviation Credit Shock for the Model Including Housing and Credit Shocks*



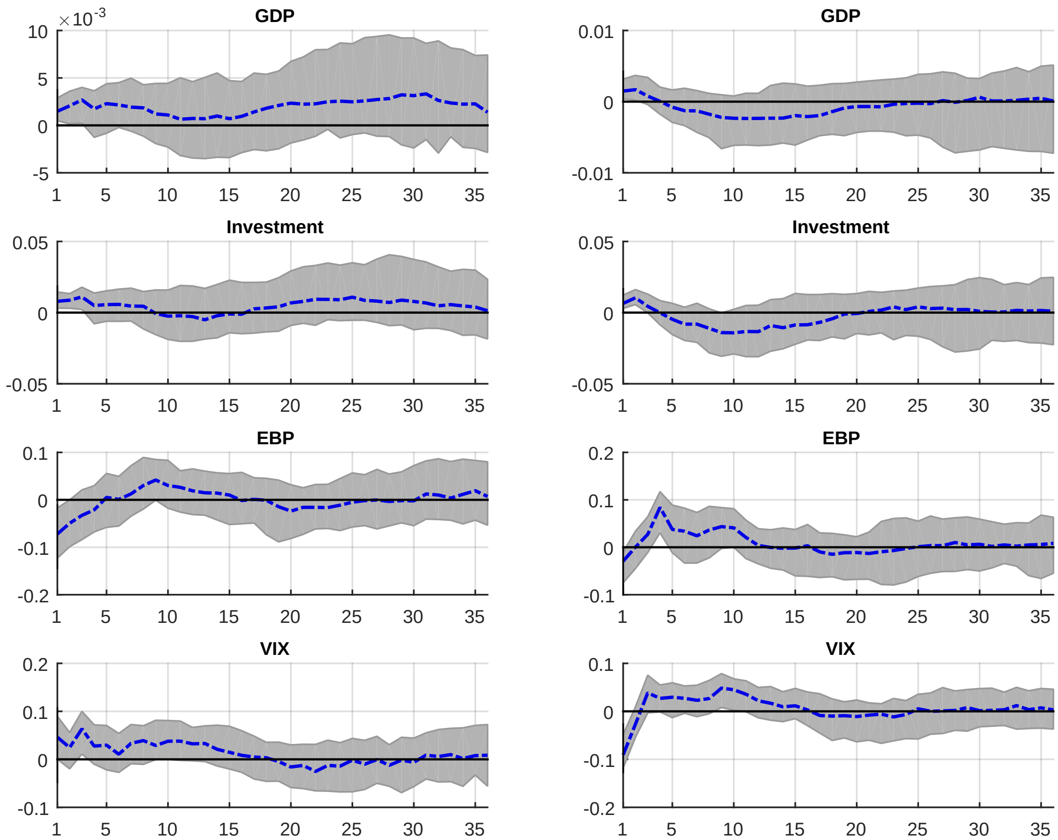
The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

Figure 6: *Impulse Responses to an One-Standard-Deviation Housing Shock for the Model Including Housing and Credit Shocks*



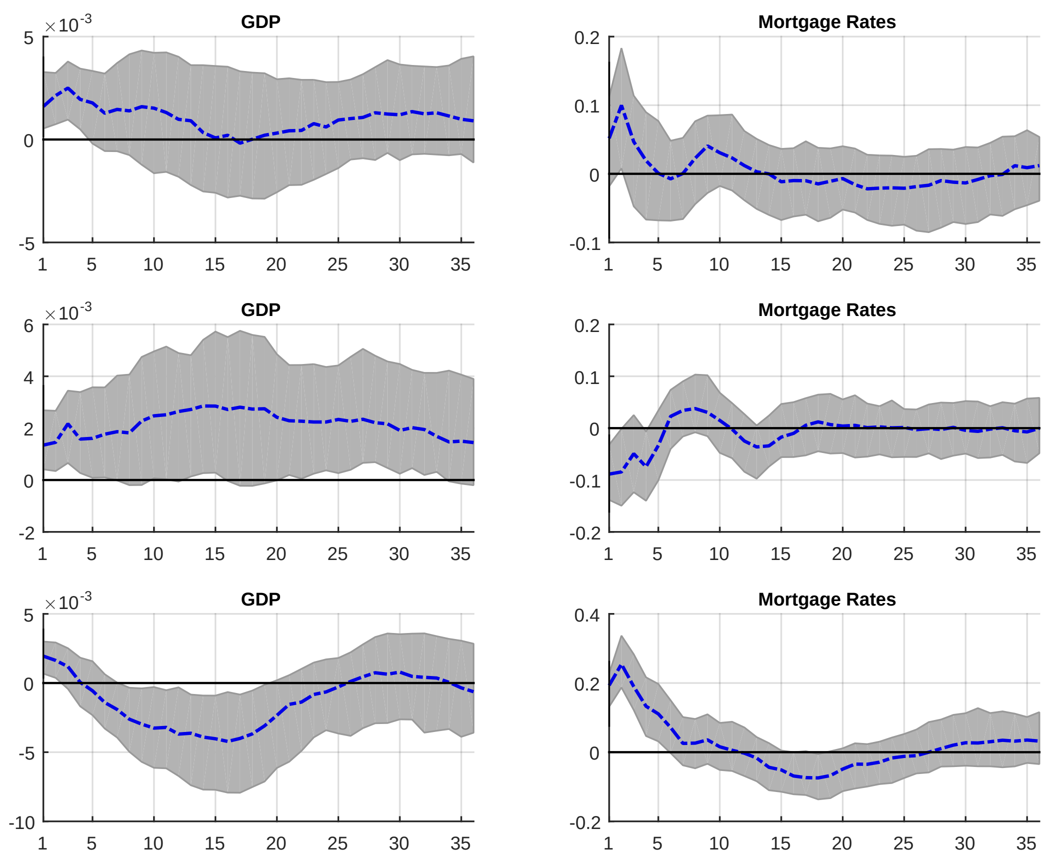
The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

Figure 7: *Impulse Responses to Credit and Uncertainty Shocks for the Model Including Housing, Credit and Uncertainty Shocks*



Impulse responses to an one-standard-deviation credit shock (left column) and uncertainty shock (right column) for the model including housing, credit and uncertainty shocks. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

Figure 8: *Impulse Responses to an One-Standard-Deviation Housing, Credit Supply and Credit Demand Shocks for the Model Including Housing, Credit Supply and Credit Demand Shocks*



Impulse responses to an one-standard-deviation housing shock (first row), credit supply shock (second row) and credit demand shock (third row) for the model including housing, credit supply and credit demand shocks. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.