Identification of financial factors in economic fluctuations*

Francesco Furlanetto[†] Francesco Ravazzolo[‡] Samad Sarferaz[§]

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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.

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†Corresponding author. Address: Norges Bank, Bankplassen 2, PB 1179 Sentrum, 0107 Oslo, Norway. E-mail: francesco.furlanetto@norges-bank.no. Telephone number: +47 22316128.

‡Address: Norges Bank and BI Norwegian Business School, Bankplassen 2, PB 1179 Sentrum, 0107 Oslo, Norway. E-mail: francesco.ravazzolo@norges-bank.no. Telephone number: +47 22316172.

§Address: ETH Zürich. E-mail: sarferaz@kof.ethz.ch. Telephone number: +41 446325432.

1 Introduction

An important role for shocks originating in the financial sector has been highlighted in the aftermath of the Great Recession. In particular, Christiano, Motto and Rostagno (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, Primiceri and Tambalotti, 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. 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 is potentially more flexible; it imposes little structure on the data; and, at the same time, can be used to discriminate between DSGE 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 explain only to a limited extent 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, Ilut, Motto and Rostagno (2010), who document that inflation is always low during stock market booms in post-war US data. Importantly, the shock generates a countercyclical response in the external finance premium that we introduce as an unrestricted variable in one of our extensions. This constitutes a validation exercise for our identification scheme given that it is a genuine feature of the data, 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 (see Justiniano, Primiceri and Tambalotti, 2014, and Liu, Wang and Zha, 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 the credit markets have larger effects than uncertainty shocks whose impact on macroeconomic variables is modest and short-lived. Importantly, the estimated investment response to uncertainty shocks exhibits the drop, rebound and overshoot dynamics described in Bloom (2009). Our result on the importance of shocks originating in the housing sector is fully consistent with Liu, Wang and Zha (2013) in the context of a DSGE model with collateral constraints at the firm level.

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 that financial shocks explain 12 per cent 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 in contrast plays a key role in our model.

A large number of papers focus on shocks originating in credit markets (loan supply shocks or credit spread shocks) and emphasize the importance of these shocks in explaining the Great Recession but also business cycle dynamics in general.[1] Fewer papers consider shocks originating in the housing market. Walentin (2013) 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, Neri and Stracca (2011) find similar results for the US and extend the analysis to the euro area. Prieto, Eickmeier and Marcellino (2013) estimate a time-varying VAR on US data over the

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

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 in recent years. Their model features richer dynamics than our model by allowing for time-varying parameters, while our model features a richer set of shocks identified with sign restrictions (rather than exclusion restrictions).

The separate identification of credit and uncertainty shocks is the subject of few recent papers. Popescu and Smets (2010) identify financial and uncertainty shocks in a VAR with recursive ordering where financial variables are affected contemporaneously by uncertainty shocks but credit shocks have only a lagged effect on uncertainty measures. They conclude that uncertainty shocks have small and temporary effects on output while shocks originating in credit markets have more long-lasting effects. Caldara, Fuentes-Albero, Gilchrist and Zakrajsek (2014) disentangle the macroeconomic implications of financial (credit) shocks and uncertainty shocks by using the penalty function approach by Faust (1998) and Uhlig (2005) to separately identify the two shocks. They find an important role for financial (credit) shocks, whereas uncertainty shocks have only a modest effect on the real economy in their benchmark specification. Our analysis confirms these results but at the same time shows that shocks originating in the housing sector are the most important financial shock to explain macroeconomic dynamics.

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 DSGE models like Smets and Wouters (2007). The second, and perhaps most important, contribution is the identification of housing shocks, credit shocks 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 one of our estimation exercises. 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, Fuerst, Ortiz and Paustian, 2013). 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 and supply shocks, acyclical or weakly countercyclical in response to investment shocks and procyclical or at best acyclical in response to monetary policy shocks, depending on the measure of the spread used in the estimation.

The paper is organized as follows. Section 2 describes the econometric model and discusses the identification strategy. Section 3 presents the results for the baseline version of our model and the results on the cyclical properties of the external finance premium. In Section 4 we present two extensions to disentangle housing, credit and uncertainty shocks. Finally, Section 5 concludes.

2 The model and the identification strategy

Consider the following reduced form VAR model:

$$y_t = C_B + \sum_{i=1}^{P} B_i y_{t-i} + u_t, \tag{1}$$

where y_t is a $N \times 1$ vector containing all N endogenous variables, C_B is a $N \times 1$ vector of constants, B_i for $i = 1, ..., P$ are $N \times N$ parameter matrices, and u_t is the $N \times 1$ one-step ahead prediction error with $u_t \sim N(0, \Sigma)$, where Σ 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 and these priors lead to a Normal-Wishart posterior, see Appendix A, with mean and variance parameters corresponding to OLS estimates.[2]

Regarding the identification procedure, the prediction error u_t can be written as a linear combination of structural innovations ϵ_t

$$u_t = A\epsilon_t$$

with $\epsilon_t \sim N(0, I_N)$, where I_N is an $(N \times N)$ identity matrix and where A is a non-singular parameter matrix. The variance-covariance matrix has thus the following structure $\Sigma = AA'$. Given the fact that the variance covariance matrix is symmetric, N(N-1)/2 further restrictions are needed to derive A from this relationship.

One popular way of imposing the required restrictions on A is to use the Cholesky decomposition. In this identification procedure the parameter matrix A is restricted to be lower triangular implying a recursive identification scheme. Although computationally very convenient, the recursive identification cannot be justified theoretically given the variables used in this paper, 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 different mapping from the reduced form innovations to the structural innovations 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 such a context, although challenging from a computational point of view. One issue with

[2]The Bayesian approach is entirely 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, see the discussion in Sims, Stock, and Watson (1990) and Sims and Uhlig (1991).

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

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). This is particularly relevant when only one shock is identified. In our paper, we identify five shocks in the baseline case, and up to six shocks in the extensions, and therefore the “multiple shocks problem” is arguably less serious.

To incorporate the sign restrictions, especially given the number of variables we include and the number of shocks to be identified at the same time, we use the efficient algorithm described in Rubio-Ramirez, Waggoner and Zha (2010).[4] The procedure works as follows. In a first step we draw 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 of $X = QR$, where X is drawn from $X \sim N(0, I_N)$. Then, we generate candidate impulse responses from AQ and 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 X and iterate over the same procedure again until the sign restrictions are satisfied.

Table 1 describes the restrictions used in our baseline VAR. Importantly, restrictions are imposed only on impact (in keeping with the recommendation of Canova and Paustian, 2011) and this is the minimum set of restrictions to achieve identification. Restrictions to identify demand, monetary and supply shocks are standard in the literature (cf. Peersman, 2005, and Peersman and Straub, 2006 among others) and are consistent with a simple three-equation New Keynesian model. 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 set restrictions on the response of the ratio of investment over output. We

[4] The estimation is conducted in MATLAB version R2010b using the parallel function over a 8-core machine with 2.93GHz. The exercise time varies from 24 hours for the baseline model to a few weeks for the larger version with six identified shocks.

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	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.

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 have a positive effect on 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 in DSGE models) or a foreign shock.[5] The imposed restrictions are satisfied in standard DSGE models like Smets and Wouters (2007) and Justiniano, Primiceri and Tambalotti (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 goal, we follow closely the discussion in Christiano, Motto and Rostagno (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 imply a positive co-movement between output and the price

[5]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".

of capital (together with the stock market). Therefore, the investment shock implies that the value of equity is countercyclical. This explains why investment shocks can be the main source of fluctuations in models that do not include financial variables (as in Justiniano, Primiceri and Tambalotti, 2010), whereas they lose importance in models that use financial variables as observable.

To summarize, 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. To the best of our knowledge our restrictions are consistent with the impulse responses for financial shocks in a large number of models (estimated or calibrated) with a financial accelerator or with collateral constraints, even in presence of substantial investment adjustment costs. This is the case for the net worth shock and the risk shock in the estimated model by Christiano, Motto and Rostagno (2014), for the shock to the firm's ability to borrow in the estimated model by Jermann and Quadrini (2012), for the housing demand shock in the estimated models by Liu, Wang and Zha (2013) and Walentin (2013), for the shock to the intermediation spread in the estimated model by Ajello (2013), for the shock to bank capital in the calibrated model by Rannenberg (2013), for the shock to bankruptcy costs in the estimated model by Fuentes-Albero (2013), for the liquidity shock in the calibrated model by Del Negro, Eggertsson, Ferrero and Kiyotaki (2011), for the shock to investor sentiment in the calibrated model by Martin and Ventura (2012), for the collateral shock in the estimated model by Liu, Wang and Zha (2013), and for the five different financial shocks considered in the estimated model by Iacoviello (2014).[6]

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. Nonetheless,

[6]Notice that our identifying assumptions are not consistent with the shocks to bank capital considered in Gerali, Neri, Sessa and Signoretti (2010) and in Meh and Moran (2010). These shocks move output and inflation in different directions and thus would be considered as a supply shock in our framework.

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 to aggregate demand that we previously mentioned. Furthermore, news shocks about future technology could in principle 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, Basu and Lee (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, Basu and Lee (2014) are supportive for our identification strategy to isolate financial shocks.

Some issues arise when summarizing the information contained in the sign-restricted impulse responses. At first glance, the median at each horizon seems to be a suitable summary measure of the accepted impulse responses. However, Fry and Pagan (2011) show that it is problematic to interpret structurally the median of sign-restricted impulse responses. In fact, taking the median across all possible draws at each horizon implies mixing impulse responses that emanate from different structural models. They suggest choosing impulse responses from the closest model to the median response instead. Inoue and Kilian (2013) argue further that the median vector in general is not an appropriate measure of central tendency within the context of sign-restricted impulse responses. Their solution involves the derivation of the posterior density of the accepted impulse responses. The modal model, which corresponds to the values that maximize the posterior density of the restricted impulses responses, is then chosen as the measure of central tendency.

In our empirical exercises we follow the early sign restriction literature and show variance decompositions that are based at each horizon on the median draw that satisfies our restrictions. However, we also present results based on different measures of central tendency as the median target proposed by Fry and Pagan (2011) and the modal model proposed by Inoue and Kilian (2013).

3 Results

In this section we present the results derived from the estimation of our baseline model and of an extension that includes the external finance premium as an unrestricted variable in the estimation. A common feature of this section is the tight link to the DSGE literature that will be in part loosened in the next section, where we will identify several kinds of financial shocks.

The model is estimated for the US with quarterly data in levels from 1985 Q1 to 2011 Q4. Since our model has constant coefficients, we prefer to concentrate on a relatively homogenous sample period that includes mainly the Great Moderation. The VAR includes 5 lags. The list of endogenous variables in the baseline model includes GDP, GDP deflator as measure of prices, interest rate, investment and stock prices. All variables except the interest rate are expressed in terms of natural logs. The data series used in all the estimation exercises are summarized in Table 5. The benchmark model has five identified shocks: supply, demand, monetary, investment and financial.

3.1 Results for the baseline model

In Figure 1 we plot the contribution of each of the five shocks identified in the benchmark model to the forecast error variance of GDP, prices, the interest rate, investment and stock prices. The variance decompositions are based at each horizon on the median draw that satisfies our sign restrictions.[7] Two shocks explain the lion's share of fluctuations in macroeconomic variables

[7] As discussed in Fry and Pagan (2011), a variance decomposition based on the median of the impulse responses combines information stemming from different models so that it 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 five shocks. See Figure 3 for two alternative measures of central tendency in which the variance decomposition does not require any normalization.

in our model: supply shocks and financial shocks. While supply shocks are the main drivers of output, financial shocks explain almost 50 percent of the variability in investment and in stock prices. Moreover, they are solid second drivers of output dynamics by explaining on average almost 30 percent 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 are important also at low frequencies where they are as important as supply shocks. While the view that low frequency fluctuations are due to supply factors (mainly labor supply) is often embedded in macroeconomic models, the importance of financial factors for low frequency dynamics has been discussed only recently (cf. Borio, 2012).

The relevance of financial shocks can also be appreciated from the impulse responses plotted in Figure 2. We see that financial shocks have a large and hump-shaped effect on output but a limited impact on prices. Moreover, the financial shock seems to be well identified although we impose our restrictions only on impact. The large effect on output and the limited effect on prices are reinforced when we consider the two alternative measures of central tendency (see Figure 3). The modal model, in particular, predicts a somewhat larger output response and a substantially smaller prices response resulting in an almost irrelevant contribution for inflation dynamics in the variance decomposition. The effects of financial shocks on output are very persistent, thus highlighting the importance of financial factors at low frequencies.

Figure 4 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. But financial shocks are also active in boom periods like the second half of the 1990s (together with positive supply shocks) and around the mid 2000s (together with positive supply, demand and monetary policy shocks). To evaluate the influence of the Great Recession, we have re-estimated the model with data until 2007-Q2. From the variance decomposition and the impulse responses in Figure 5, we see that financial shocks maintain a sizeable role, although as expected they explain a lower share of output fluctuations. Importantly, financial shocks are almost irrelevant for inflation dynamics over the period 1985-2007.

While the result on the importance of financial shocks for output fluctuations has been discussed elsewhere in the literature, the limited response of prices to financial shocks is a new result of this paper. Our result can be used to interpret why inflation was surprisingly low during stock market and credit booms in the US (cf. Christiano, Ilut, Motto and Rostagno, 2010)[8] and why inflation was surprisingly high in the aftermath of the Great Recession given the size of the contraction in output and employment (cf. among others Beaudry and Portier, 2013). Our model describes the three stock market boom periods identified by Christiano, Ilut, Motto and Rostagno (2010) included in our sample (1985-1987, 1994-2000, 2003-2007) as periods characterized 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 adjustments in inflation. Christiano, Ilut, Motto and Rostagno (2010) rationalize their unconditional evidence through the lenses of a DSGE model driven by news shocks about future technology. In our model the news shocks about technology are considered as positive supply shocks that, in fact, are important drivers of GDP during stock market booms. However, according to our model financial shocks are also important. The limited drop in inflation during and after the Great Recession is discussed in Del Negro, Giannoni and Shornfheide (2013). They attribute the low decline in inflation to the presence of very stable inflation expectations (together with a rather high degree of price rigidity) and show that a New Keynesian model *with* financial frictions estimated using data on inflation expectations can successfully replicate inflation and output dynamics.[9] Gilchrist,

[8]Christiano, Ilut, Motto and Rostagno (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.

[9]Primiceri (2013) shows that a standard New Keynesian model *without* financial frictions and financial shocks grossly overestimates inflation over the stock market boom periods identified by Christiano, Ilut, Motto and Rostagno (2010) and grossly underestimates inflation in the recent period. The better performance of the model

Schoenle, Sim and Zakrajsek (2013) also investigate inflation dynamics in the Great Recession. They propose a New Keynesian model with customer markets and a simple form of financial frictions and show that financially constrained firms have the incentive to increase prices in response to a negative demand shock. Gilchrist, Schoenle, Sim and Zakrajsek (2013) stress the role of financial frictions in the propagation of other disturbances, whereas we concentrate more on the role of financial factors as a source of shocks.

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 6 presents the median impulse responses for each variable in response to supply, demand, monetary and investment shocks. The supply shock generates large effects on output but also on investment and stock prices that are left unrestricted in the estimation. These effects are consistent with the dynamics induced by a standard technology shock in DSGE models.[10] Monetary shocks have a protracted positive effect on output. Nonetheless, according to our model the macroeconomic relevance of monetary policy shocks seems to be limited. We do not find any systematic response of the stock market to monetary policy shocks. This is interesting in light of the debate opened by Gali' and Gambetti (2014) 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. In keeping with Christiano, Motto and Rostagno (2014), the inclusion of financial variables in the model crowds out the investment shock, which maintains limited explanatory power. Demand shocks have small effects on output, investment and the stock market but are the main driver of prices.

While our general financial shock is consistent with many different kind of financial shocks, in

by Del Negro, Giannoni and Shorfheide (2013) suggests that taking into account financial frictions and financial shocks may be important to capture inflation dynamics.

[10]However, it is important to recognize that the supply shock captures 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 labor market, such as labor supply, wage mark-up and matching efficiency shocks.

Appendix B we concentrate our attention on the two financial shocks considered by Christiano, Motto and Rostagno (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, Motto and Rostagno (2014). These risk shocks are often interpreted as the DSGE equivalent of the uncertainty shocks identified by Bloom (2009) and the subsequent VAR literature. We will explore further the link between uncertainty shocks and other kinds of financial shocks in section 4.2.

3.2 Evidence on the external finance premium

So far we have shown that financial shocks are important (for output dynamics) and non-inflationary. We now want to show that our estimated financial shocks are also plausible. In this context an important validation exercise concerns the response of the spread (or external finance premium) that we expect to be countercyclical. We introduce a spread measure in the estimation and leave its response to shocks unrestricted. Since we introduce an additional variable, we also include an extra shock with undefined economic interpretation. We repeat the exercise with three different measures of the external finance premium that have been used extensively in the literature: the GZ spread based on corporate bond yields and constructed by Gilchrist and Zakrajsek (2012), the difference between yields on BAA bonds and the Federal Funds rate, and the difference between yields on BAA bonds and 10-year government bonds. Figure 7 plots the median response of the different measures of the premium to the five identified shocks. Importantly, the response to a financial shock is strongly countercyclical for the three spread measures, thus validating our estimated financial shock.

The inclusion of the external finance premium in the estimation is not useful only as a validation exercise. In fact, 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. Since we leave the response of the premium to shocks unrestricted in our model, our results are potentially useful to discriminate between different DSGE models and, as far as we know, this is the first paper that provides conditional empirical evidence on the premium response. According to our model the premium is countercyclical in response to supply and demand shocks, acyclical or weakly countercyclical in response to investment shocks, and procyclical or, at best, acyclical in response to monetary policy shocks, depending on the measure of the spread.

In the DSGE literature the response of the premium 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 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 generates a procyclical premium in response to a monetary policy shock is the financial accelerator model with a debt contract indexed to aggregate conditions, as in Carlstrom, Fuerst, Ortiz and Paustian (2013). Moreover, that model is also consistent with our evidence for investment and financial shocks.

4 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 want to 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 on the magnitude rather than on the sign of the responses.

Since we increase the number of identified financial shocks, we need to sacrifice one of the non-financial shocks for computational reasons. We choose to remove the monetary policy shock. 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 and are therefore difficult to identify. 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.

4.1 Housing shocks and credit shocks

In our first 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 phenomenon like house preference shocks, bubbles in real estate markets, credit market liberalizations or relaxations in credit standards. 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

Table 2: 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 to real estate	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.

example of a shock originating in the credit markets is the shock to the loan to value ratio in models with collateral constraints (cf. Liu, Wang and Zha, 2013, and Justiniano, Primiceri and Tambalotti, 2014, among others). 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 disentangle the two shocks.[11] In the VAR literature, starting with Jarocinski and Smets (2008), the standard assumption is that shocks originating in credit markets have a zero impact effect on house prices and on macroeconomic variables (like inflation and GDP) whereas shocks originating in the housing market have an immediate effect on variables related to credit markets (like credit spreads or mortgage rates), but still have a zero impact effect on macroeconomic variables.

We follow an alternative route to 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 (see Table 2). 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

[11] 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 (2013) shows that the use of investment adjustment costs, rather than capital adjustment costs as in Iacoviello and Neri (2010), favors a positive response of business investment. Furthermore, Liu, Wang and Zha (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.

have used to identify our general financial shock in Section 3, 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 house prices has to be lower than the increase in credit. This is in keeping with a large literature summarized in Justiniano, Primiceri and Tambalotti (2014) 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 or by a bubble in the real estate sector). Our restriction allows credit to increase on the impact of the shock, but its increase has to be lower than the one in house prices. While an increase in collateral values driven by a housing boom certainly calls for an expansion in credit, we assume that on the impact of the shock this endogenous relaxation of lending standards has to be limited. The use of data on total credit to the private sector (rather than only on mortgages as in Justiniano, Primiceri and Tambalotti, 2014) makes our identifying assumption less restrictive. 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.

The variance decomposition in Figure 8 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 3 (although housing shocks now have a somewhat larger effect on inflation). From impulse responses in Figures 9 and 10 we see that the restrictions on the credit to real estate ratio are satisfied over several quarters for both shocks even though we impose them only on impact. The effects of housing shocks are large and very persistent, whereas the impact of credit shocks is more short-lived.

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, Wang and Zha (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 per cent of the fluctuations in output with the housing shock alone explaining more than 20 percent of output fluctuations. Justiniano, Primiceri and Tambalotti (2014) 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.

At this stage it is important to stress that our housing shock may have several interpretations. So far we have emphasized the link with housing demand shocks or with bubbles in the real estate sector but other stories can be consistent with the dynamics induced by our housing shock. 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. This restriction is very informative (although imposed only on impact) and might be a useful starting point to further disentangle financial shocks.

To test the robustness of our result on the importance of housing shocks, we present some extensions. First, we focus on household credit (rather than total credit) and we re-estimate the model by using data on the mortgage to real estate ratio to parallel the discussion in Justiniano, Primiceri and Tambalotti (2014). The results are largely unaffected, thus suggesting that the specific measure of credit is not central to explain the dominant role of the housing shock (see Figure 12). Second, we re-estimate the model by excluding the Great Recession from the sample period. In the shorter sample the role of housing shocks is slightly reduced, thus highlighting the key role of housing sector in the Great Recession (see Figure 12). In that experiment the non-inflationary role of financial shocks that we discussed in the our baseline model reemerges.

Finally, 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 have re-estimated our model by imposing the restriction on the credit to real estate value at horizon 4 (rather than on impact) but the results are virtually unaffected. Furthermore, in our last robustness check we have imposed 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. Not surprisingly, credit shocks become now somewhat more important for business cycle fluctuations (cf. Figure 13). Nevertheless, the housing shock is still the most important financial shock, thus confirming the main result of our baseline model.

4.2 Housing shocks, credit shocks and uncertainty shocks

The dynamics induced by the credit shock identified in the previous sub-section look similar to the ones induced by the risk (uncertainty) shock mentioned in Section 3.1 (and more extensively in Appendix B). This is not necessarily surprising given that data on credit are used to identify both shocks. Nevertheless, it points out that disentangling credit and uncertainty shocks may be empirically challenging. In addition, our estimated credit shock exhibits the drop, rebound and overshoot dynamics that Bloom (2009) describes as typical of uncertainty shocks. Therefore, we believe it would be particularly interesting to overcome the identification problem and separately identify credit, housing and uncertainty shocks in the same set-up.

Caldara, Fuentes-Albero, Gilchrist and Zakrajsek (2014) manage to separately identify the two shocks by relying on the penalty function approach originally proposed by Faust (1998) and Uhlig (2005). In their set-up the two shocks are identified using the criterion that each shock should maximize the response of a target variable over a given horizon. The target variable is the excess bond premium (EBP) measure constructed by Gilchrist and Zakrajsek (2012) for the credit shock and several proxies of macroeconomic uncertainty (realized stock market volatility, VIX, in the baseline case) for the uncertainty shock. In this section we also approach the issue of the identification of credit and uncertainty shocks by using the EBP series and a measure of stock market volatility to identify the shocks. However, we do not rely on the penalty function approach. Instead, we rather impose sign restrictions on the ratio of these financial variables. We assume that expansionary credit and uncertainty shocks both lower the EBP on impact. To achieve identification we impose 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.[12] 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 our identification procedure is that the order of the variables does not matter for identification purposes, unlike in the penalty function approach.

[12]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. One additional shock with no economic interpretation is included in the system to match the number of variables and shocks.

Table 3: 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	NA	-	+	+	+
Credit to real estate	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.

Importantly, in our set-up uncertainty shocks and credit shocks are estimated together with the other shocks discussed in the previous sections and all the restrictions are summarized in Table 3. In particular, we are interested in the role of the housing shock in a set-up where more financial variables are used in the estimation.

We plot the variance decomposition for this exercise in Figure 14. The main result is that 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. The impulse responses to a housing shock (plotted in Figure 15) confirm that the persistent effects induced by the shock are the main driver of output, investment, stock prices and credit to real estate ratio. EBP and VIX, that are left unrestricted in the estimation, both tend to decrease on the impact of the shock. In the short-run both credit and uncertainty shocks play an important role, so that the sum of the three financial shocks explain on average more than 50 percent of fluctuations in output, investment and stock prices. 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 low frequencies are at play. The non-inflationary effect of financial shocks highlighted in Section 3 is also present here, at least for horizons lower than 10 quarters. In a nutshell, the key results discussed in the previous sections are confirmed in this more elaborate set-up with an even larger role for financial shocks (and housing shocks in particular).

Let us now turn to the analysis of credit and uncertainty shocks, which constitutes the key insight of this section (see Figures 16 and 17 for the 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, although 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. The investment response to uncertainty shocks closely match the drop, rebound and overshoot behavior described in Bloom (2009), thus giving credibility to our identification strategy.

More generally, we find strong support for the main result in Caldara, Fuentes-Albero, Gilchrist and Zakrajsek (2014), who highlight the macroeconomic relevance of financial (credit) shocks and downplay the importance of uncertainty shocks. However, it is worth highlighting a few differences that distinguish our results. First, our VAR assigns a larger role to both credit and uncertainty shocks at short horizons. Second, while our variance decomposition squares quite well with the assumptions of the penalty approach,[13] all macro shocks induce some fluctuations in VIX and EBP in our framework with a special role for housing shocks. Third, we do not identify a drop in VIX in response to a positive credit shock. In our analysis VIX and EBP are positively correlated in response to uncertainty shocks but are less so conditional on credit shocks (in particular on impact).

[13]The VIX variable is in fact mainly explained by uncertainty shocks and the credit shocks play a large role in EBP dynamics, especially at short horizons.

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 have considered 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 have considered three different financial shocks (housing, credit and uncertainty shocks) identified on the basis of restrictions on 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 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 three 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, our results confirm the drop, rebound and overshoot dynamics induced by uncertainty shocks (Bloom, 2009) but at the same time downplay the importance of these shocks for macroeconomic dynamics once other kind of financial disturbances are considered. It would be interesting to reconsider our results in the context of non-linear models where uncertainty shocks may be better identified. Third, our last exercise shows that at least 40 per cent of VIX fluctuations at short horizon and at least 70 per cent 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. Our results highlight an important endogenous component driven by financial and macro shocks. Disentangling the endogenous and exogenous component in proxy measures of uncertainty seems to be of paramount importance for future research.

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Appendix

A Bayesian Estimation of the VAR

We estimate the reduced form VAR model using Bayesian methods as discussed in e.g. Uhlig (1994), Kadiyala and Karlsson (1997), Canova (2007), and Koop, Poirier, and Tobias (2007). The VAR model described in Section 2 can be rewritten as:

$$\mathbf{Y} = \mathbf{X}\mathbf{B} + \mathbf{U}, \tag{2}$$

where $\mathbf{Y} = [y_1 \; \dots \; y_T]'$, $\mathbf{B} = [C_B \; B_1 \; \dots \; B_p]'$, $\mathbf{U} = [u_1 ... u_T]'$, and

$$\mathbf{X} = \begin{bmatrix} 1 & y_0' & \dots & y_{-p}' \\ \vdots & \vdots & \vdots & \vdots \\ 1 & y_{T-1}' & \dots & y_{T-p}' \end{bmatrix}.$$

Vectorizing equation (2) leads to:

$$\mathbf{y} = (I_n \otimes \mathbf{X})\beta + \mathbf{u}, \tag{3}$$

where $\mathbf{y} = vec(\mathbf{Y})$, $\beta = vec(\mathbf{B})$, $\mathbf{u} = vec(\mathbf{U})$, and with $vec()$ denoting columnwise vectorization. The error term $\mathbf{u}$ follows a normal distribution with a zero mean and variance-covariance matrix $\Sigma \otimes I_T$.

The likelihood function in $\mathbf{B}$ and Σ can be expressed as:

$$L(B, \Sigma) \propto |\Sigma|^{-\frac{T}{2}} \exp\left\{-\frac{1}{2}(\beta - \hat{\beta})'(\Sigma^{-1} \otimes \mathbf{X}'\mathbf{X})(\beta - \hat{\beta})\right\} \exp\left\{-\frac{1}{2} tr(\Sigma^{-1} S)\right\},$$

where $S = ((\mathbf{Y} - \mathbf{X}\hat{\mathbf{B}})'(\mathbf{Y} - \mathbf{X}\hat{\mathbf{B}}))$ and $\hat{\beta} = vec(\hat{\mathbf{B}})$ with $\hat{\mathbf{B}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$.

By using a diffuse prior for β and Σ that is proportional to $|\Sigma|^{-(n+1)/2}$ the posterior is

$$p(B, \Sigma|y) \propto |\Sigma|^{-\frac{T+n+1}{2}} \exp\left\{-\frac{1}{2}(\beta - \hat{\beta})'[\Sigma^{-1} \otimes \mathbf{X}'\mathbf{X}](\beta - \hat{\beta})\right\} \exp\left\{-\frac{1}{2}tr(\Sigma^{-1}S)\right\}, \qquad (4)$$

where y denotes all available data. It can be shown that the posterior in equation (4) is the product of a normal distribution for β conditional on Σ and an inverted Wishart distribution for Σ (see, e.g. Kadiyala and Karlsson, 1997). We hence draw β conditional on Σ from

$$\beta|\Sigma, y \sim N(\hat{\beta}, \Sigma \otimes (\mathbf{X}'\mathbf{X})^{-1})$$

and Σ from

$$\Sigma|y \sim IW(S, \nu),$$

where $\nu = (T - n) * (p - 1)$ and N representing the normal distribution and IW the inverted Wishart distribution.

B Stock market shocks and uncertainty shocks

In this extension we disentangle shocks originating in the stock markets from uncertainty shocks. As an example of a shock originating in the stock markets we consider the net worth shock originally introduced by Gilchrist and Leahy (2002), whereas as an example of an uncertainty shock we consider the risk shock introduced by Christiano, Motto and Rostagno (2014).

An exogenous increase in asset prices has a positive direct effect on entrepreneurs' net worth in models with a financial accelerator. A robust implication of net worth shocks is that an increase in net worth moves output and credit in opposite directions. As shown by Christiano, Motto and Rostagno (2014), higher net worth is associated with a lower need for external funds and thus lower borrowing. This effect is also present in the estimated model by Fuentes-Albero (2013) and in the calibrated model by Rannenberg (2013), who combines a

Table 4: Restrictions in the extended model with stock market and uncertainty shocks

	Supply	Demand	Investment	Net worth	Risk
GDP	+	+	+	+	+
Prices	-	+	+	+	+
Investment/Output	NA	-	+	+	+
Stock Prices	NA	NA	-	+	+
Credit	NA	NA	NA	-	+

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

financial accelerator on the firm side together with one on the bank side.

The risk shock is a shock to the magnitude of idiosyncratic uncertainty in the transformation of raw capital into effective capital. Christiano, Motto and Rostagno (2014) show that this shock i) is important, ii) that it generates a positive comovement between output and credit and iii) that its empirical properties resemble those of the shock identified by Bloom (2009).

Both the net worth and the risk shocks are consistent with the identification restrictions imposed on financial shocks in our baseline model. Therefore, to disentangle the two we use data on credit and we impose that risk shocks move output and credit in the same direction while net-worth shocks move output and credit in opposite directions (see restriction in Table 4). In Figure 18 we plot the variance decomposition for the extended model with two financial shocks in which we remove the monetary policy shocks for computational reasons. We remark that all the results highlighted in the baseline model are broadly confirmed. The explanatory power of the monetary policy shock is inherited by the supply shock and the sum of the two financial shocks is broadly equivalent to the importance of the general financial shock identified in the baseline model. Among the two financial shocks, we see that the risk shock is the most important, in particular at high frequencies. From the impulse responses presented in Figures 19 and 20 we see that the effect of the net worth shock is limited but very persistent. The risk shock has large, hump-shaped effects and is rather short-lived on output, investment and the stock market. Credit on the other hand responds very persistently to the shock.

All in all, our results are in line with Christiano, Motto and Rostagno (2014). They find a larger role for risk shocks, although in their framework the risk shock has also an anticipated component which is very important (cf. also Pinter, Theodoridis and Yates, 2013). In our model the risk shock is instead fully unanticipated.

Table 5: Data and Sources

Variable	Description	Source
GDP	Log of Real GNP/GDP (ROUTPUT13Q3)	Federal Reserve Bank of Philadelphia
GDP Deflator	Log of Price Index for GNP/GDP (P13Q3)	Federal Reserve Bank of Philadelphia
Interest Rate	3-Month Treasury Bill (TB3MS)	Federal Reserve Bank of St. Louis - FRED
Investment	Log of Real Gross Private Domestic Investment (GPDIC96)	Federal Reserve Bank of St. Louis - FRED
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
Mortgage	Home Mortgages of Households and Nonprofit Organizations	Board of Governors of the Federal Reserve System
Real Estate Value	Households and Nonprofit organizations (Real Estate at Market Value)	Board of Governors of the Federal Reserve System
Corporate Bond Yield	Moody's Seasoned Baa Corporate Bond Yield (BAA)	Federal Reserve Bank of St. Louis - FRED
10y Treasure Note	10-Year Treasury Constant Maturity Rate (DGS10)	Federal Reserve Bank of St. Louis - FRED
Federal Funds Rate	Federal Funds Rate	Federal Reserve Bank of St. Louis - FRED
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)

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

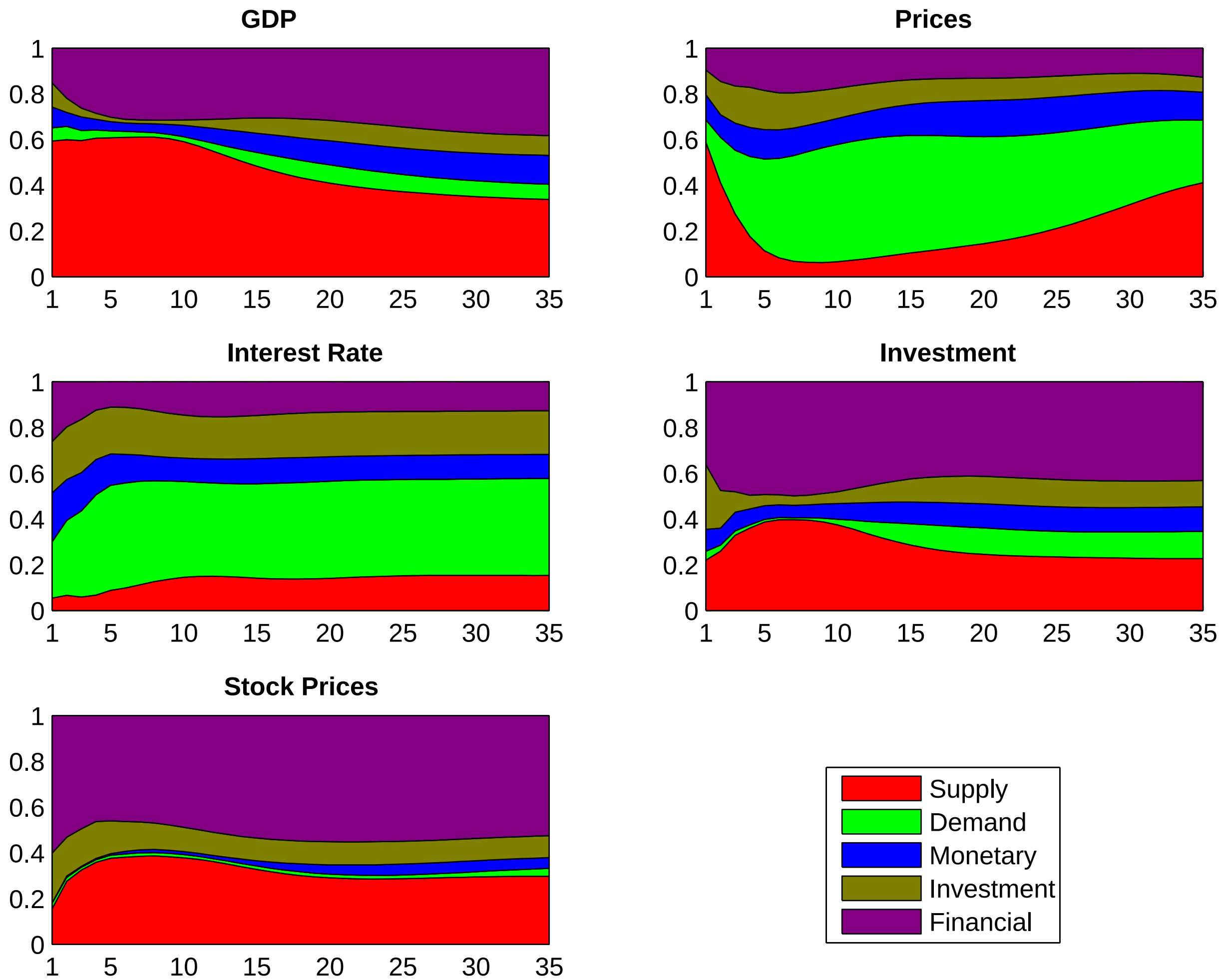

Figure 1: Median forecast error variance decompositions at each horizon for the baseline model.

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

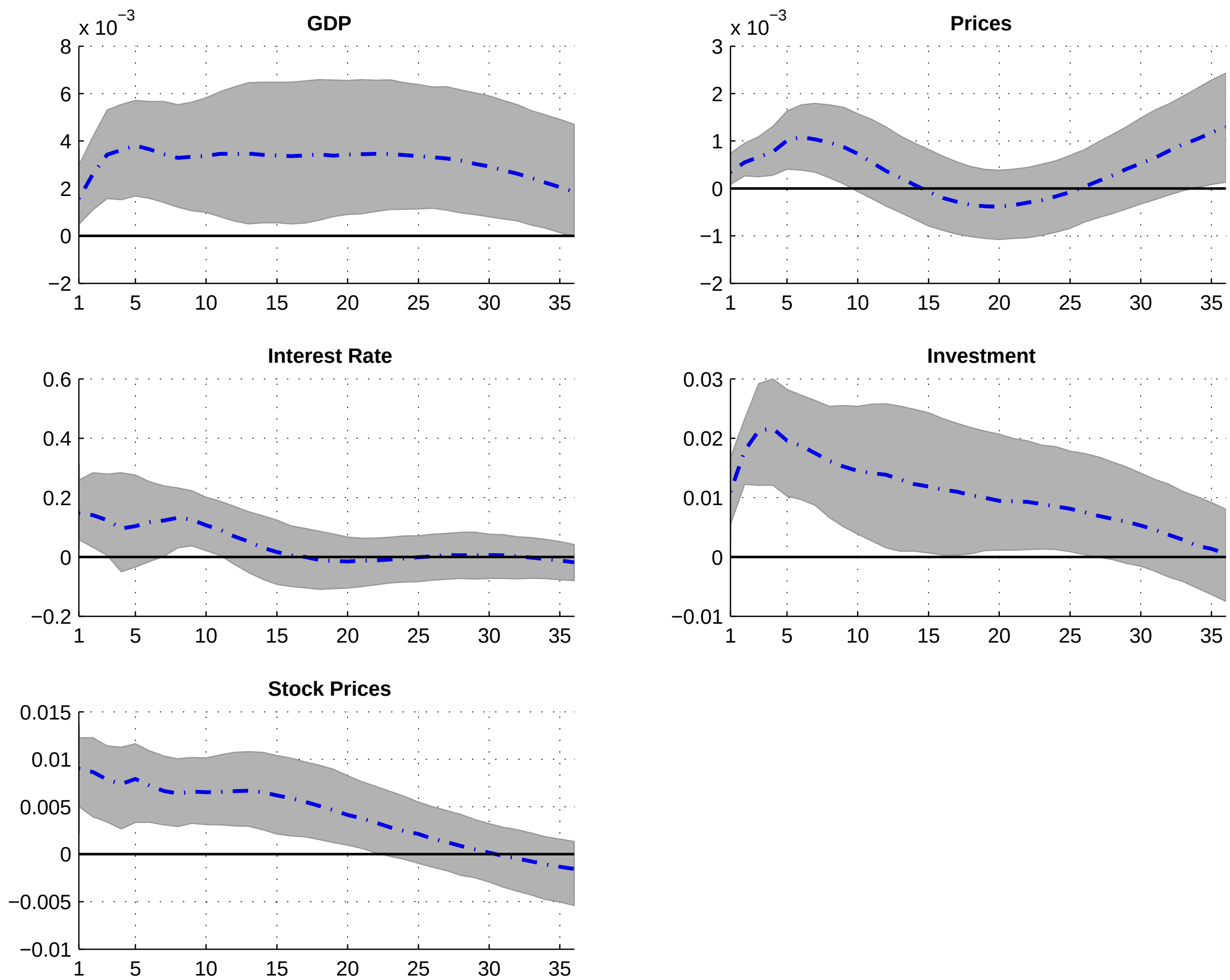

Figure 2: Impulse responses for the baseline model to an one-standard-deviation financial shock. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 16th and 84th percentiles of the impulse responses.

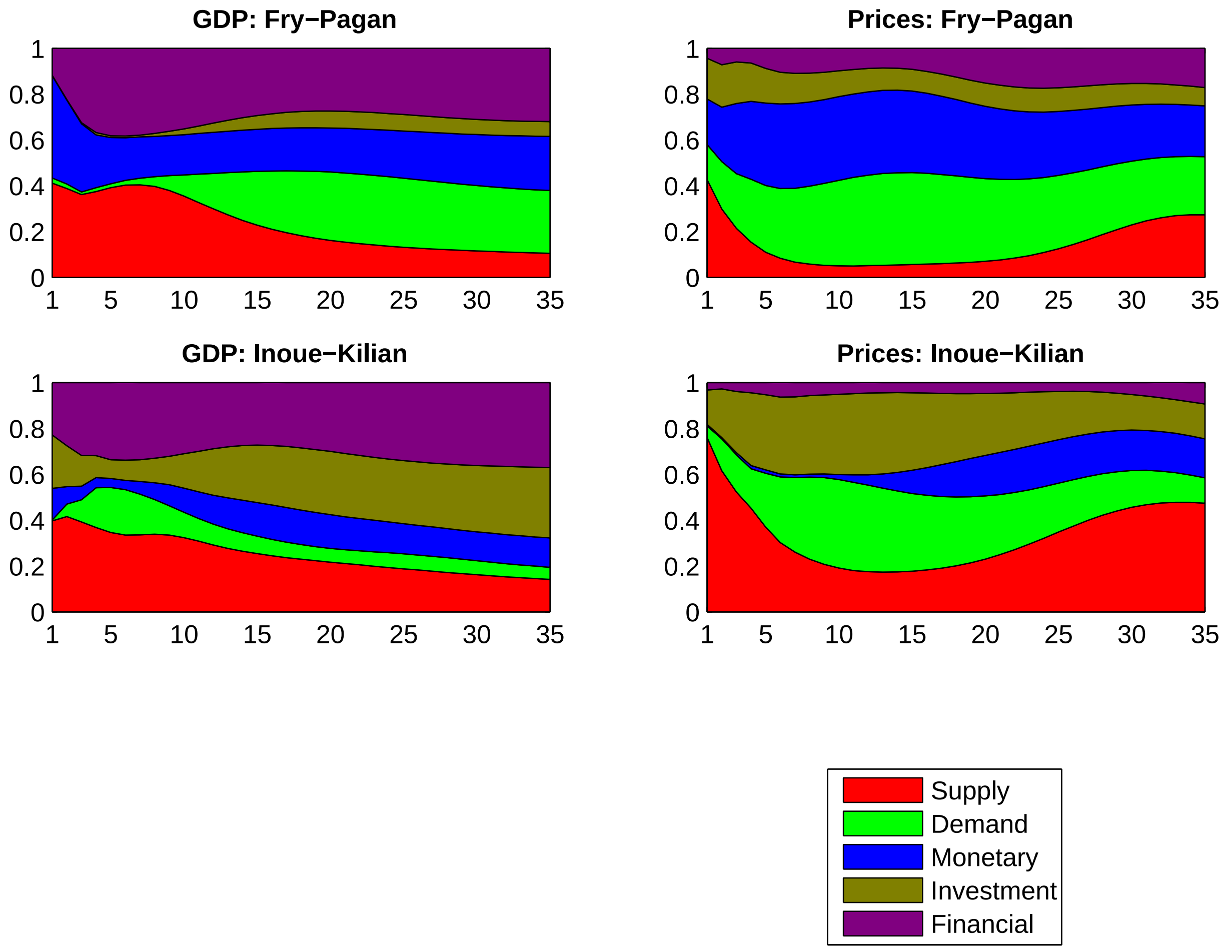

Figure 3: Forecast error variance decompositions at each horizon for the different measures of central tendency. The first row shows the forecast error variance decompositions when applying the Fry-Pagan measure of central tendency and the second row depicts the variance decomposition obtained with the Inoue-Kilian approach.

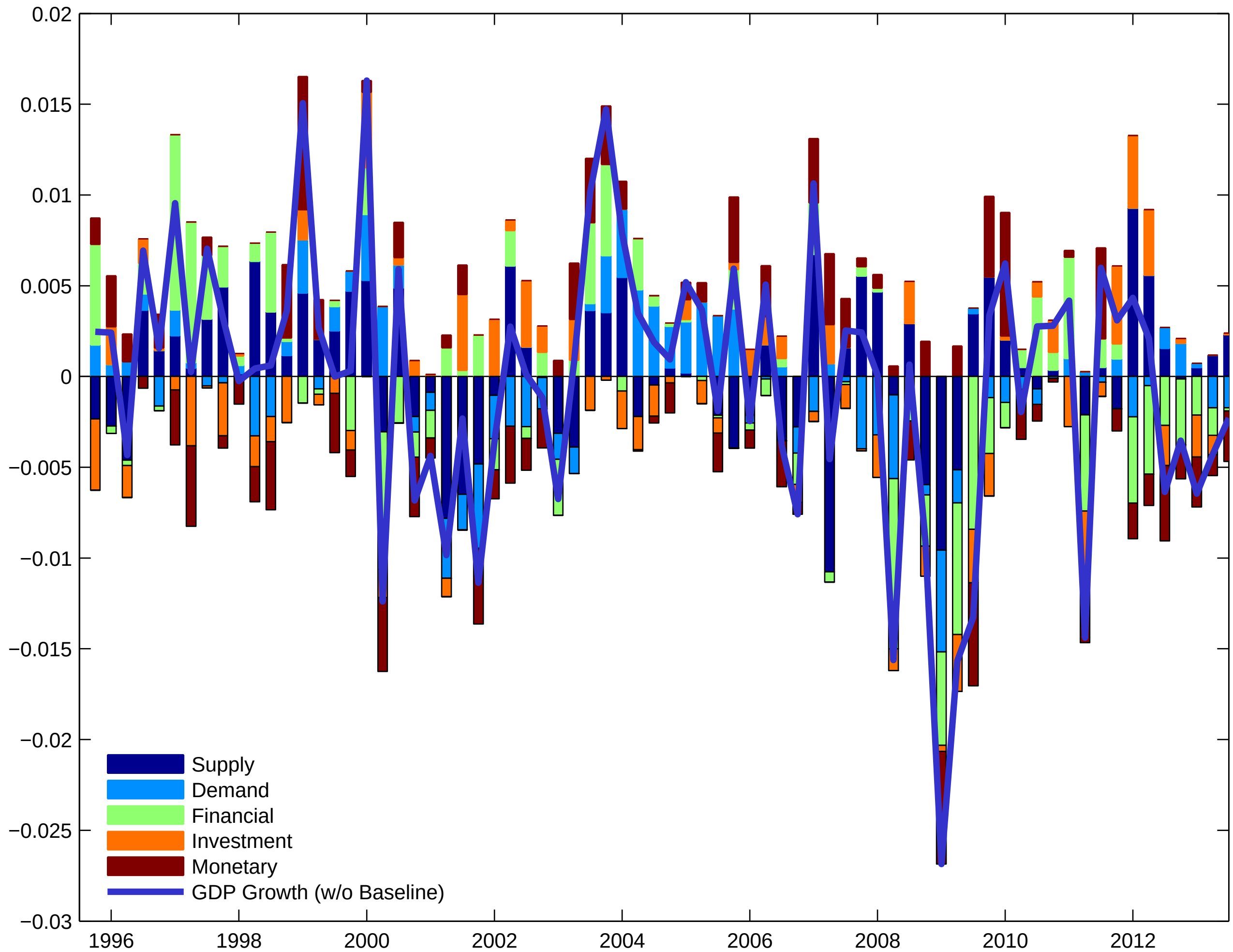

Figure 4: Contribution of shocks to deviations in GDP growth from its baseline forecast after 36 quarters for the period 1995-2013.

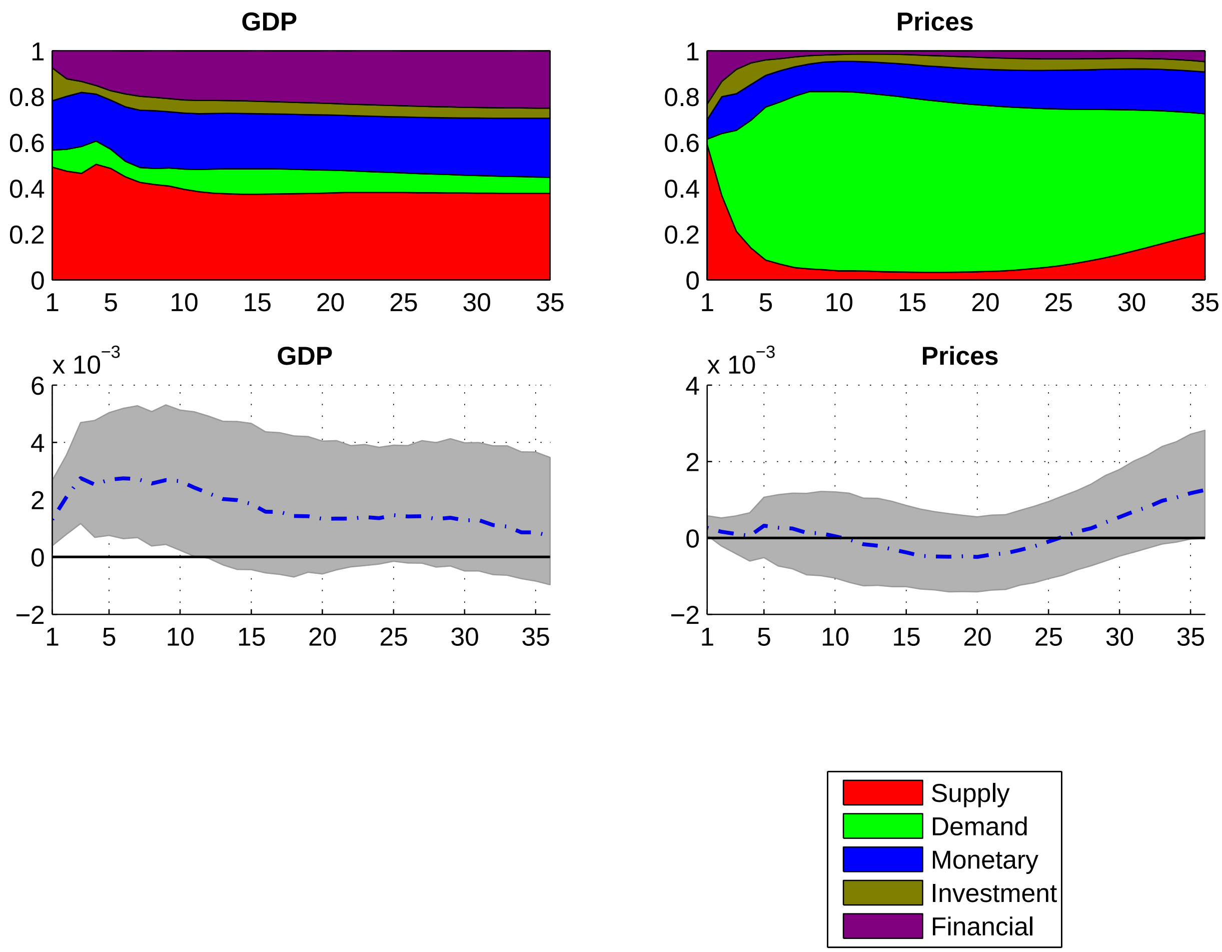

Figure 5: Impulse responses to an one-standard-deviation financial shock and the corresponding forecasts error variance decompositions using data from 1985 to 2007 for the baseline model. The first row presents the forecast error variance decompositions at the posterior median. The second row depicts the impulse responses to a financial shock where the dashed-dotted lines represent the median at each horizon and the shaded areas indicate the 16th and 84th percentiles of the impulse responses.

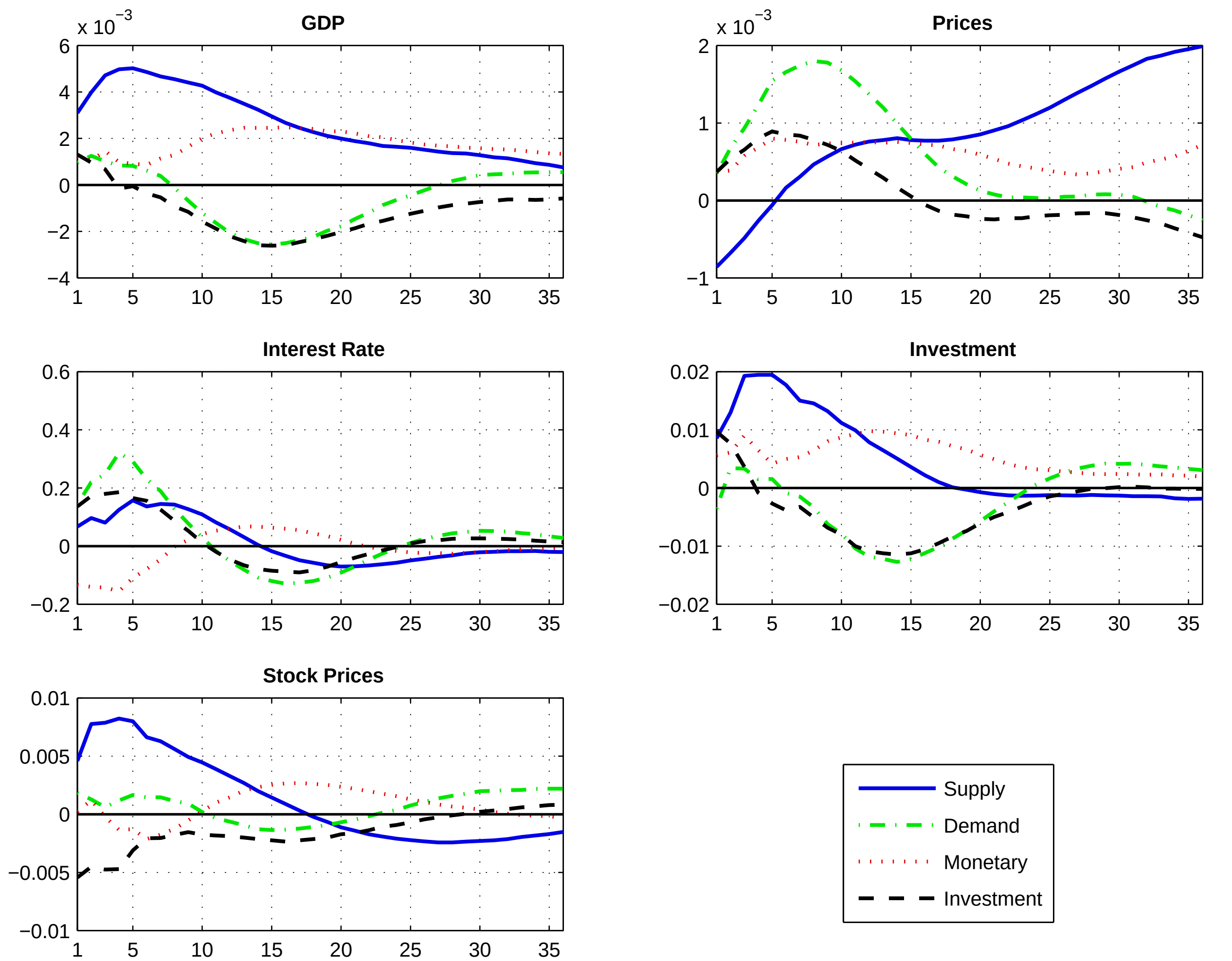

Figure 6: Median impulse responses for the baseline model to an one-standard-deviation supply, demand, monetary, and investment shock.

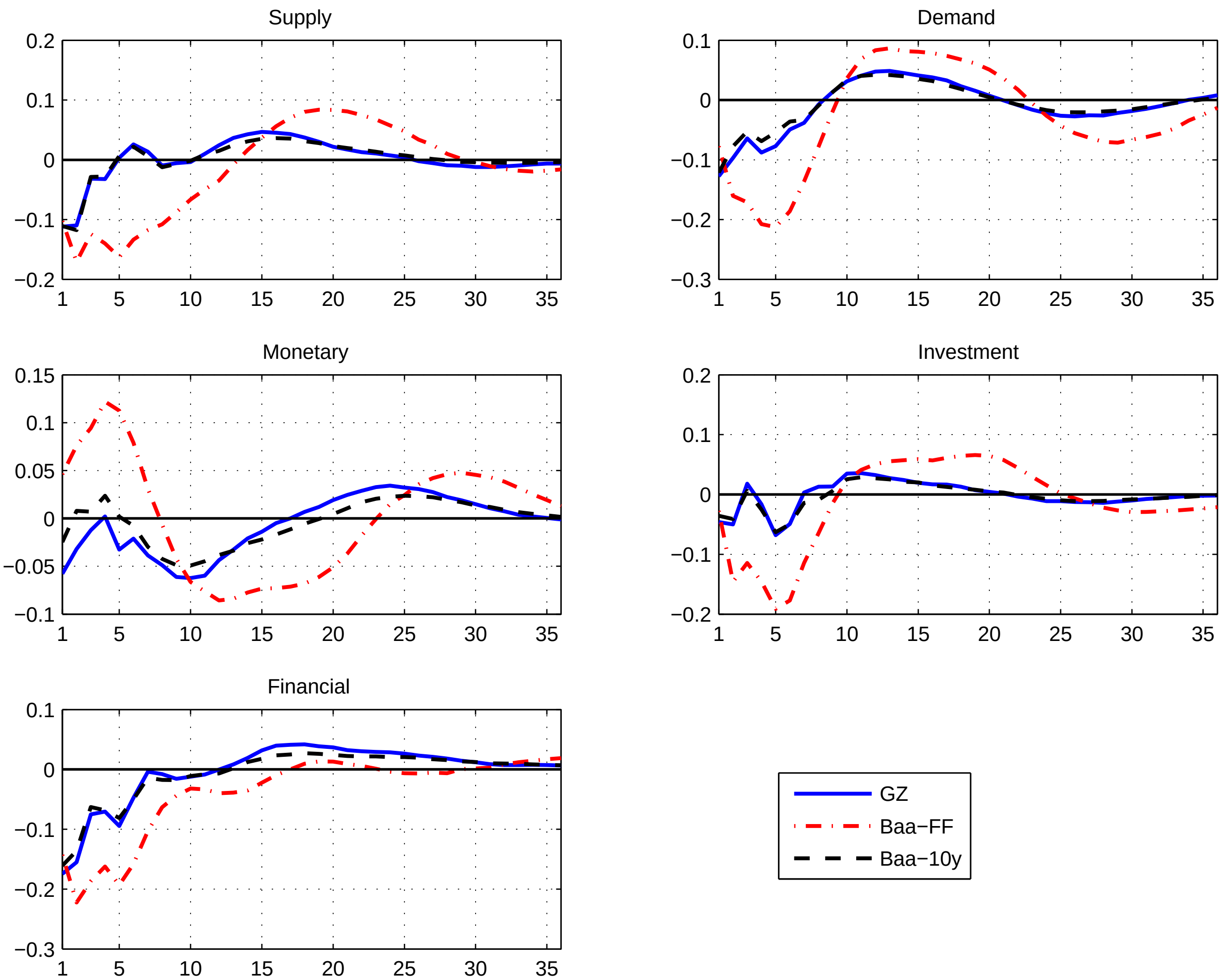

Figure 7: Median impulse responses to an one-standard-deviation financial shock with three different measures (the Gilchrist-Zakrajsek spread, the Baa - federal funds rate spread, and the Baa - 10-year Treasury note spread) of the external finance premium.

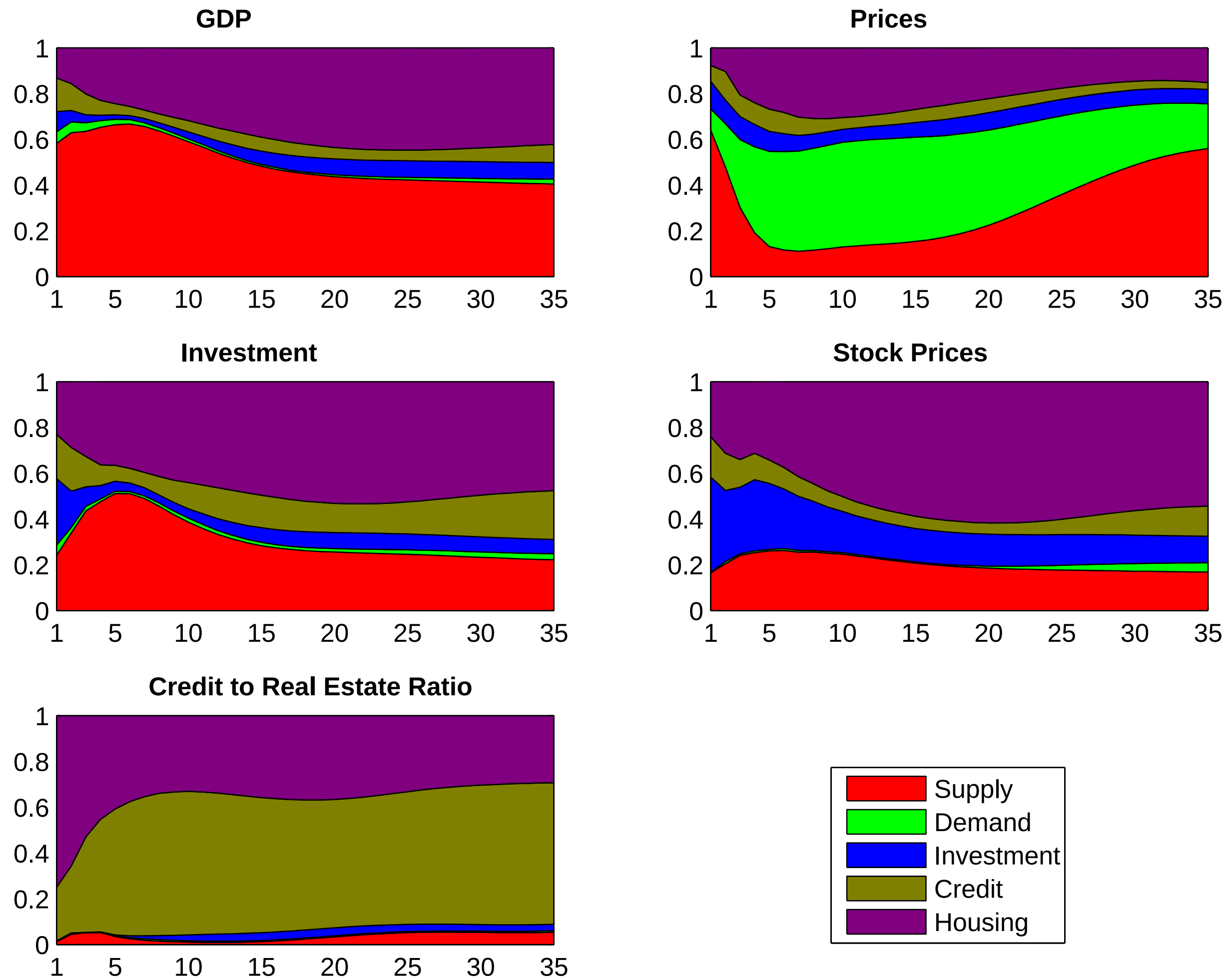

Figure 8: Median forecast error variance decompositions at each horizon for the model including housing and credit shocks.

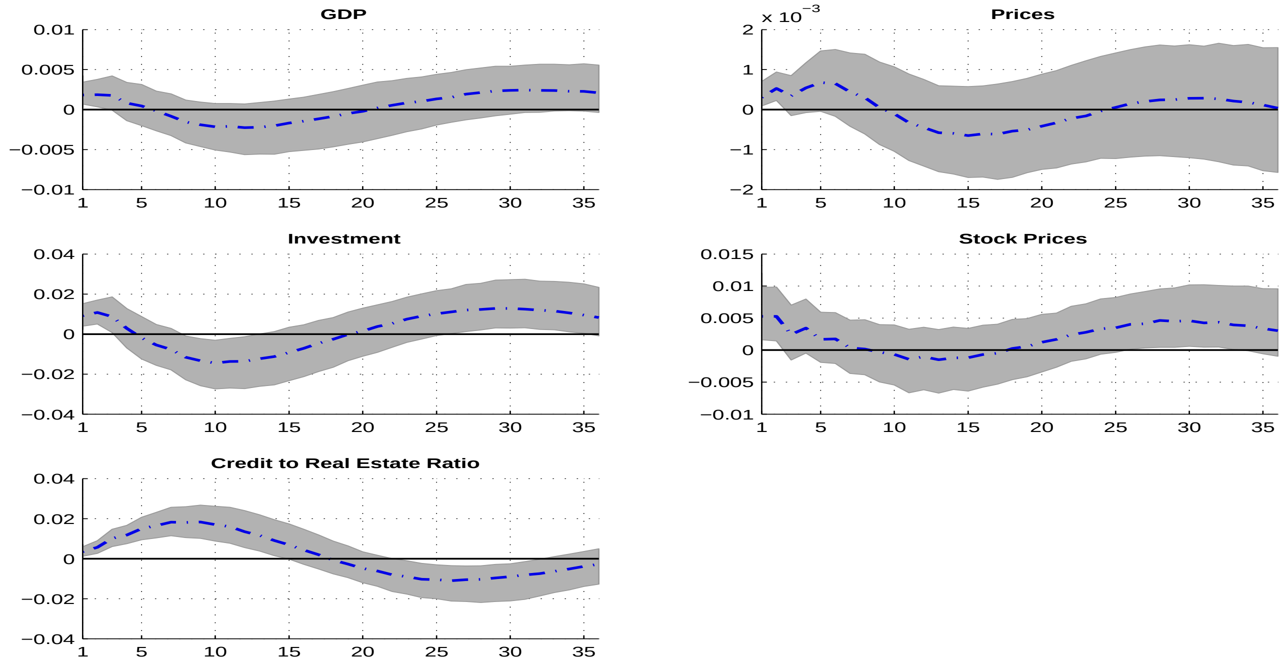

Figure 9: Median impulse responses to an one-standard-deviation credit shock for the model including housing and credit.

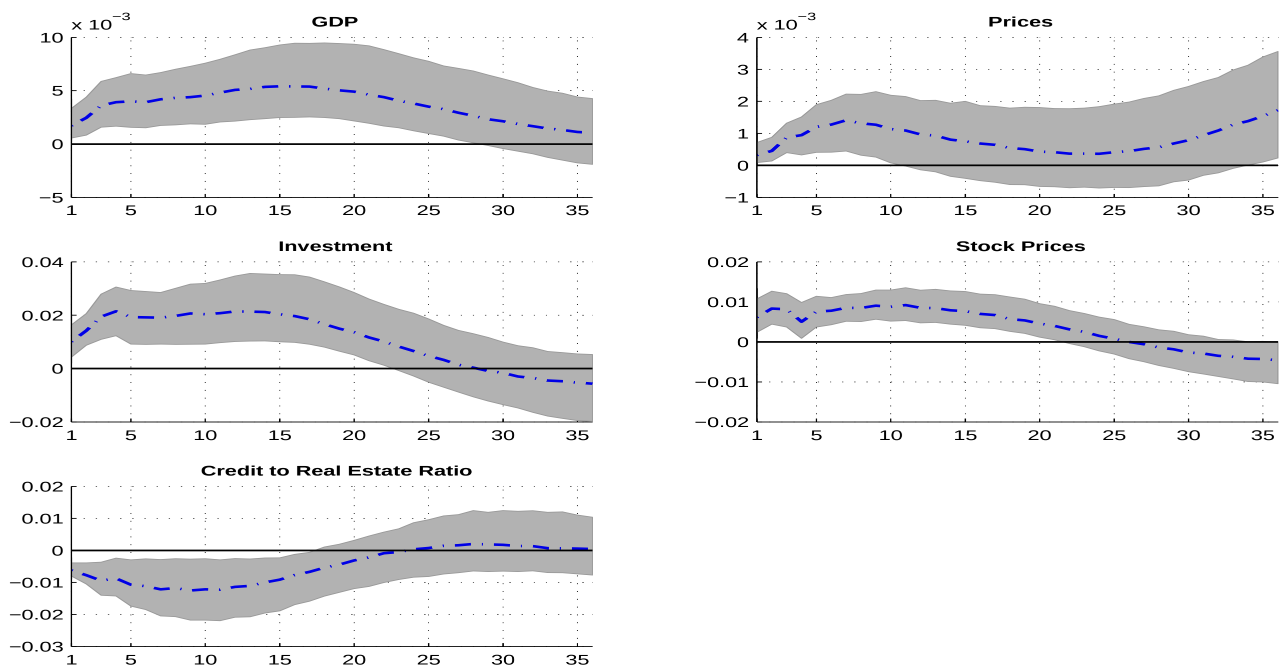

Figure 10: Median impulse responses to an one-standard-deviation housing shock for the model including housing and credit.

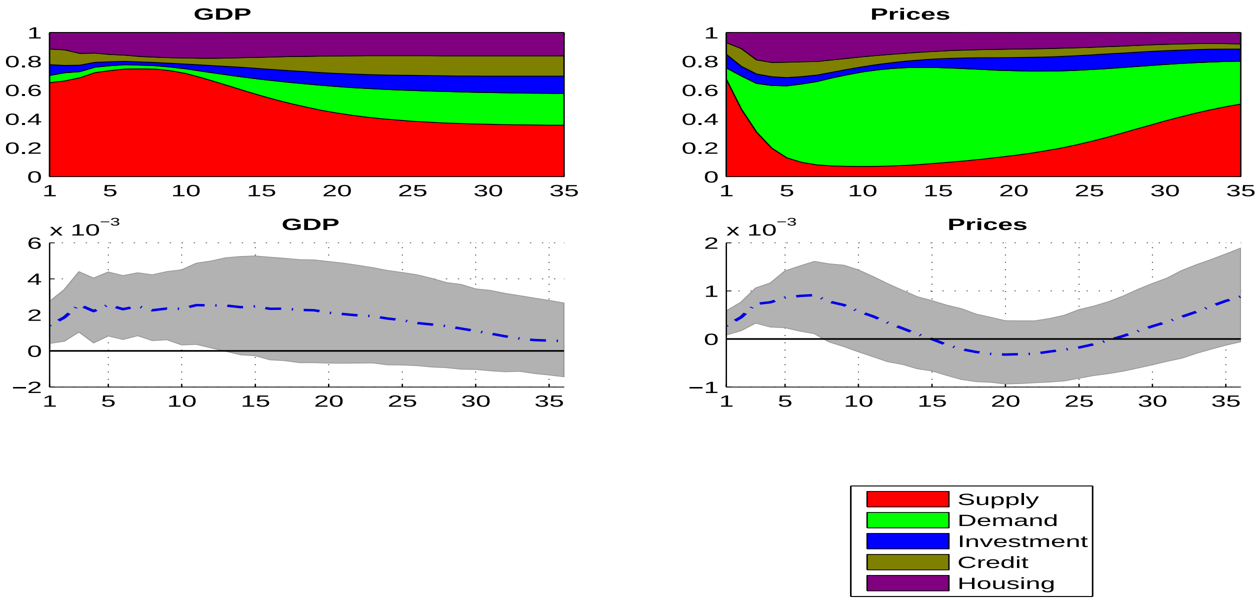

Figure 11: Impulse responses to an one-standard-deviation housing shock and the corresponding forecast error variance decompositions using the mortgage to real estate ratio for the model including housing and credit. The first row presents the forecast error variance decompositions at the posterior median. The second row depicts the impulse responses to a housing shock where the dashed-dotted lines represent the median at each horizon and the shaded areas indicate the 16th and 84th percentiles of the impulse responses.

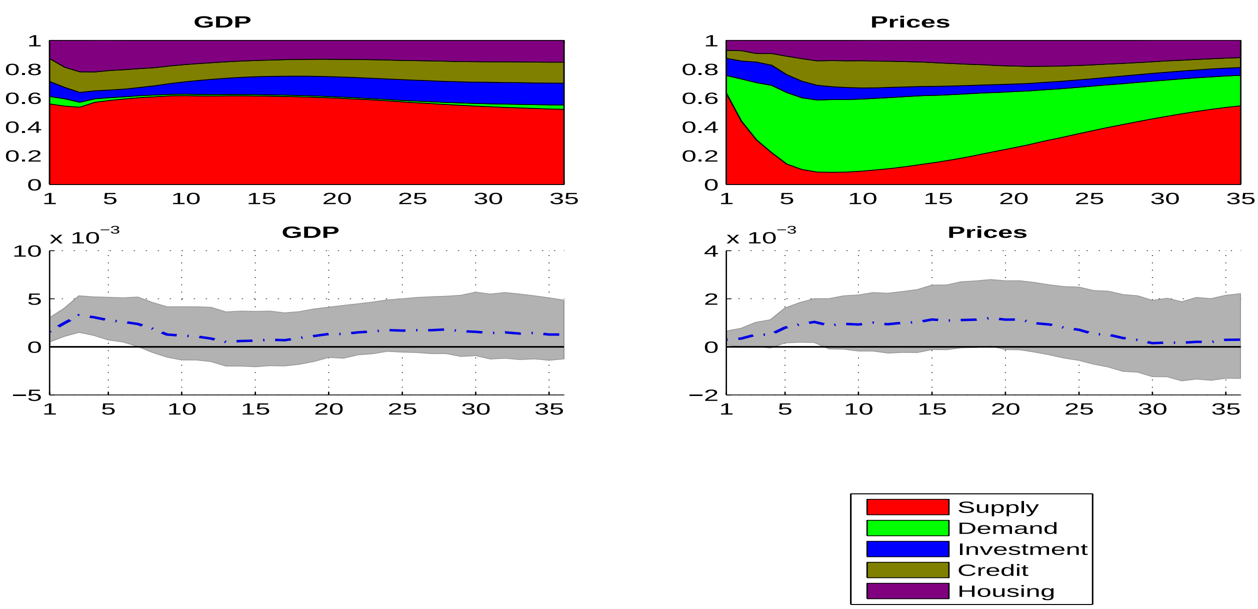

Figure 12: Impulse responses to an one-standard-deviation housing shock and the corresponding forecast error variance decompositions using data from 1985 to 2007 for the model including housing and credit. The first row presents the forecast error variance decompositions at the posterior median. The second row depicts the impulse responses to a housing shock where the dashed-dotted lines represent the median at each horizon and the shaded areas indicate the 16th and 84th percentiles of the impulse responses.

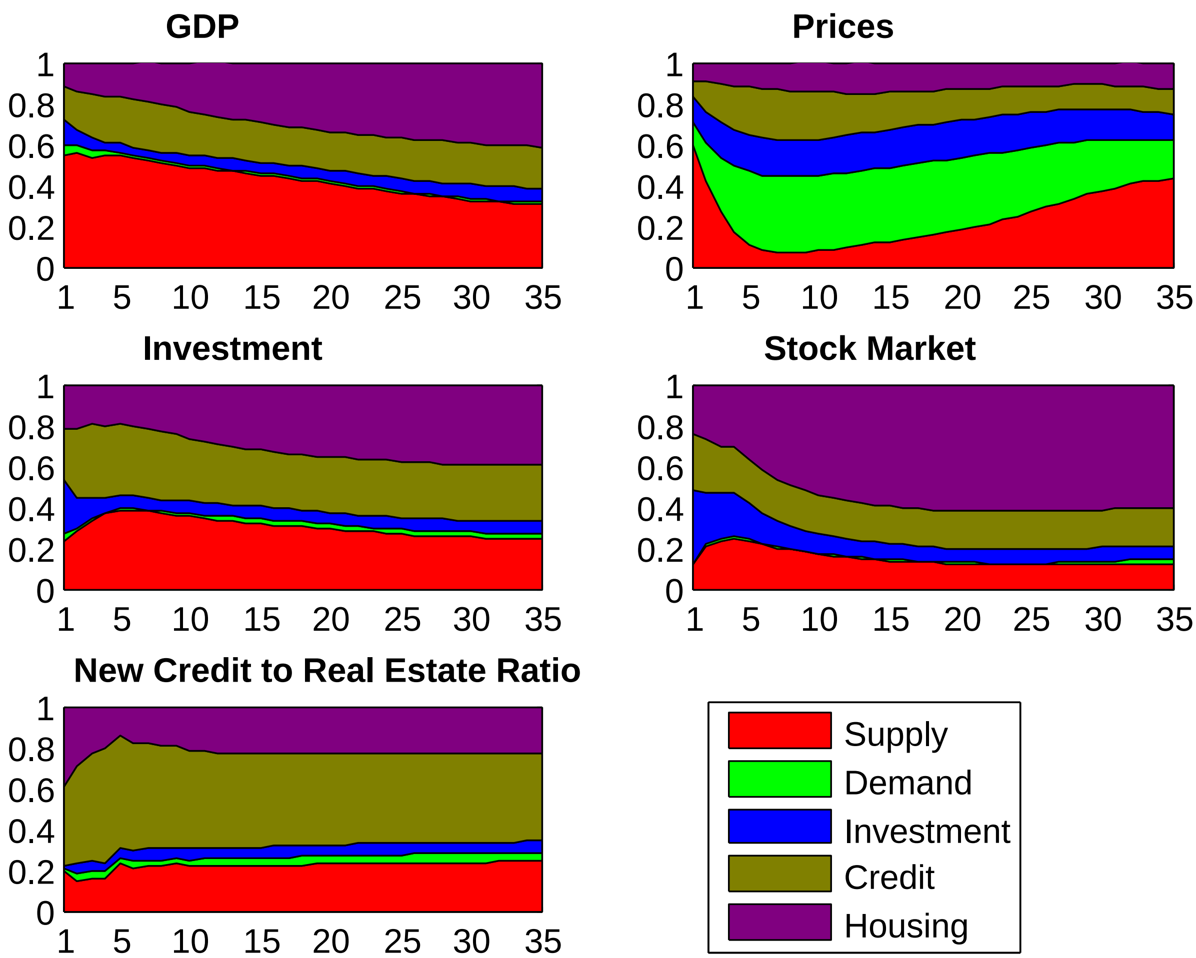

Figure 13: Median forecast error variance decompositions at each horizon for the model including housing and credit shocks.

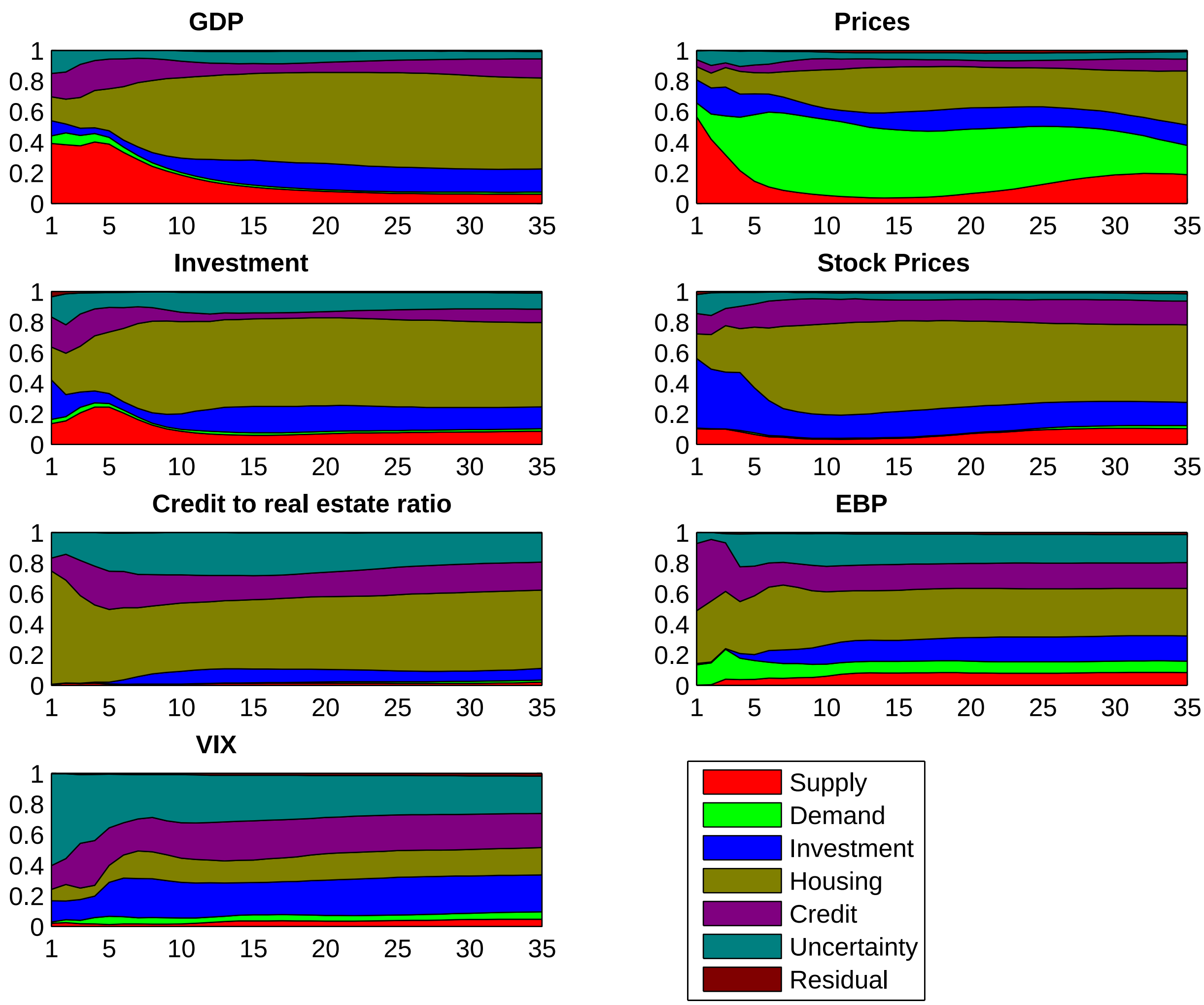

Figure 14: Median forecast error variance decompositions at each horizon for the model including housing, credit and uncertainty shocks.

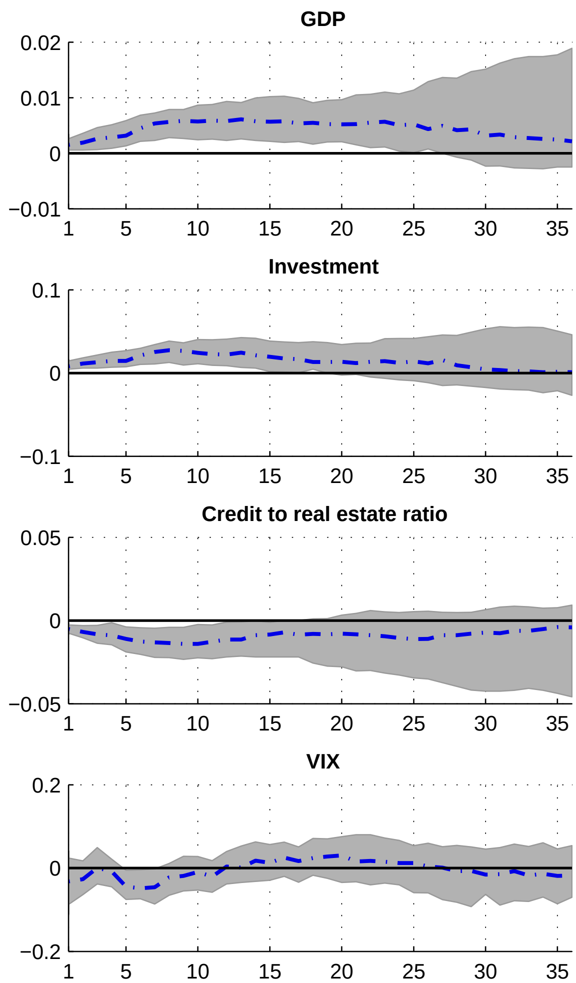

Figure 15: Median impulse responses to an one-standard-deviation housing shock for the model including housing, credit and uncertainty shocks.

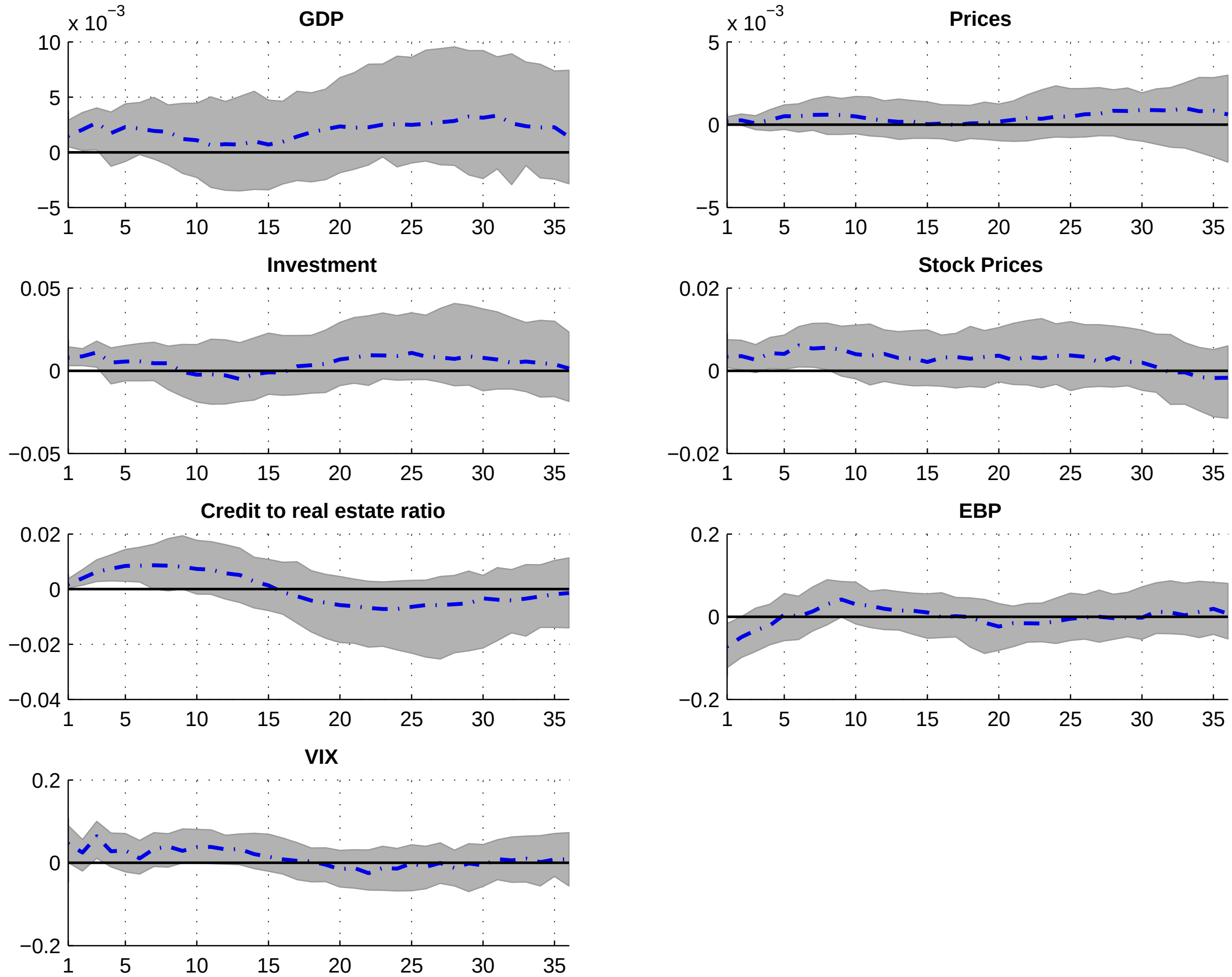

Figure 16: Median impulse responses to an one-standard-deviation credit shock for the model including housing, credit and uncertainty shocks.

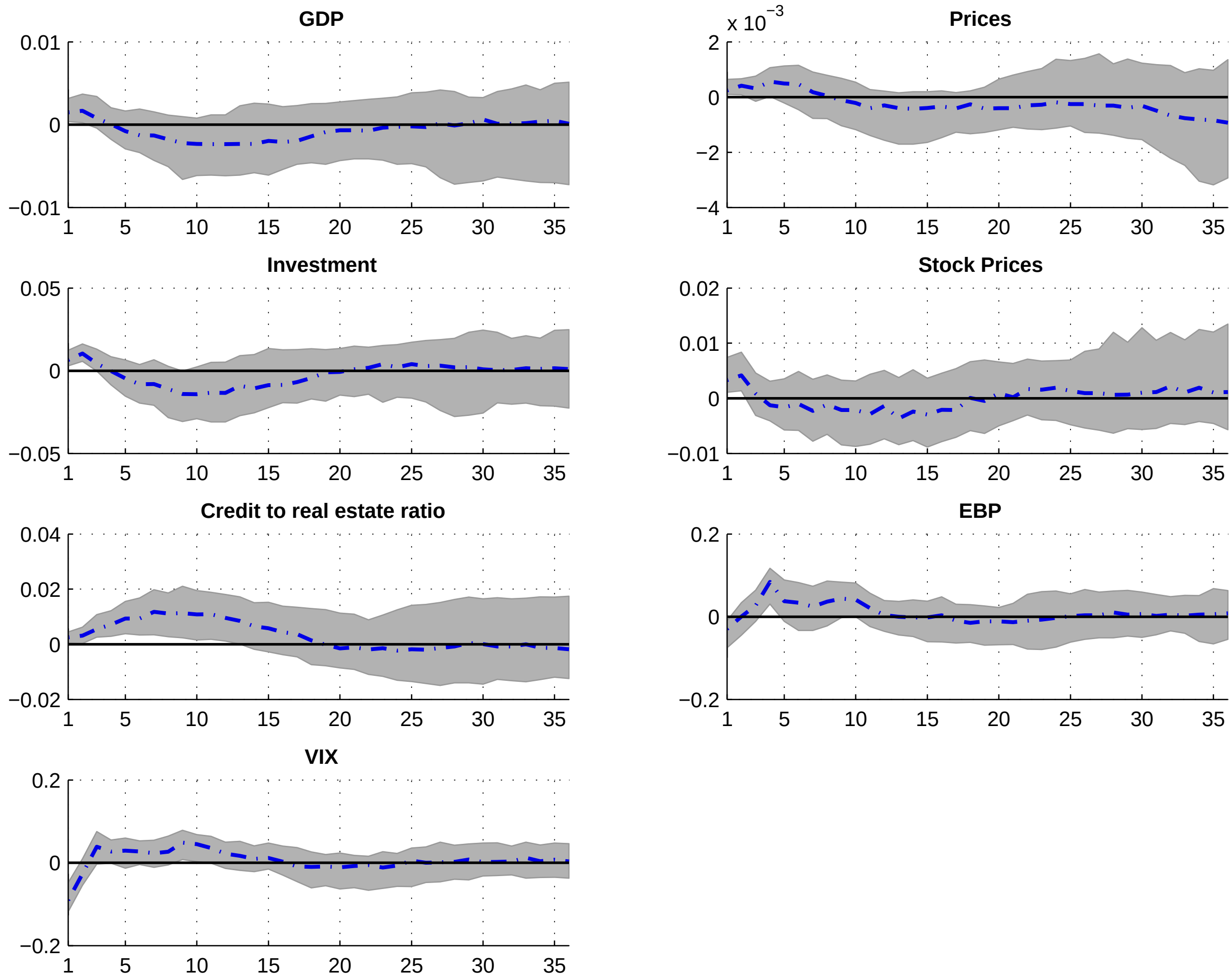

Figure 17: Median impulse responses to an one-standard-deviation uncertainty shock for the model including housing, credit and uncertainty shocks.

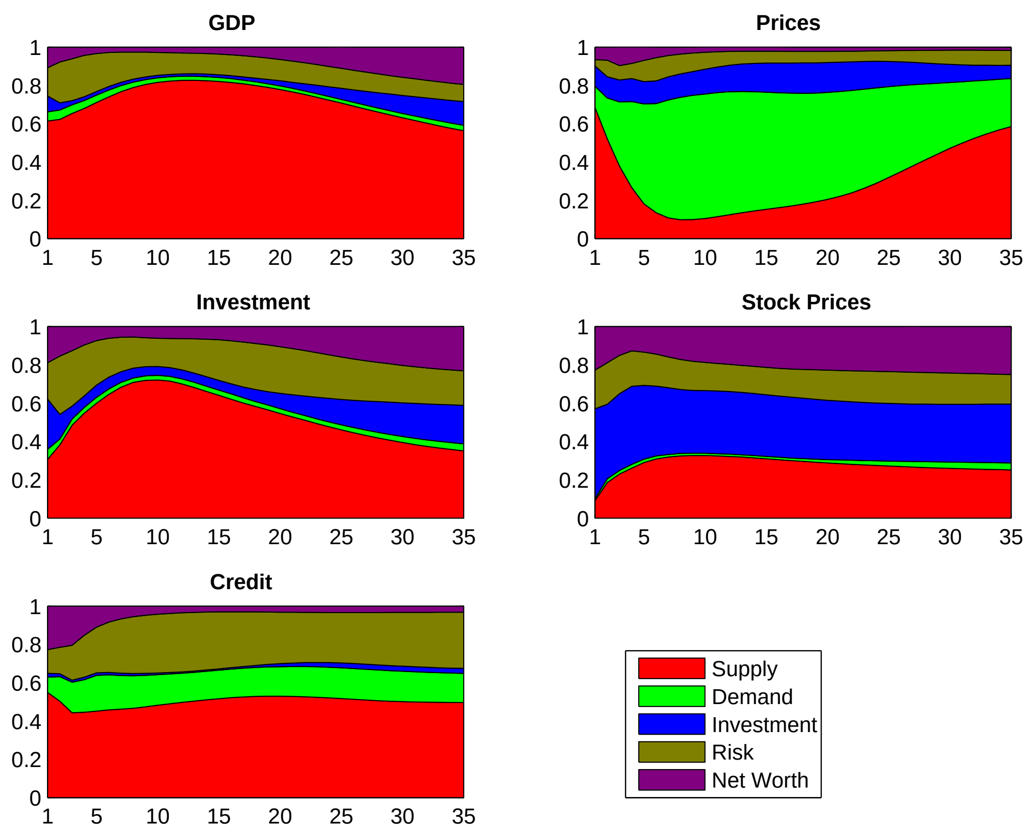

Figure 18: Median forecast error variance decompositions at each horizon for the model including risk and net worth shocks.

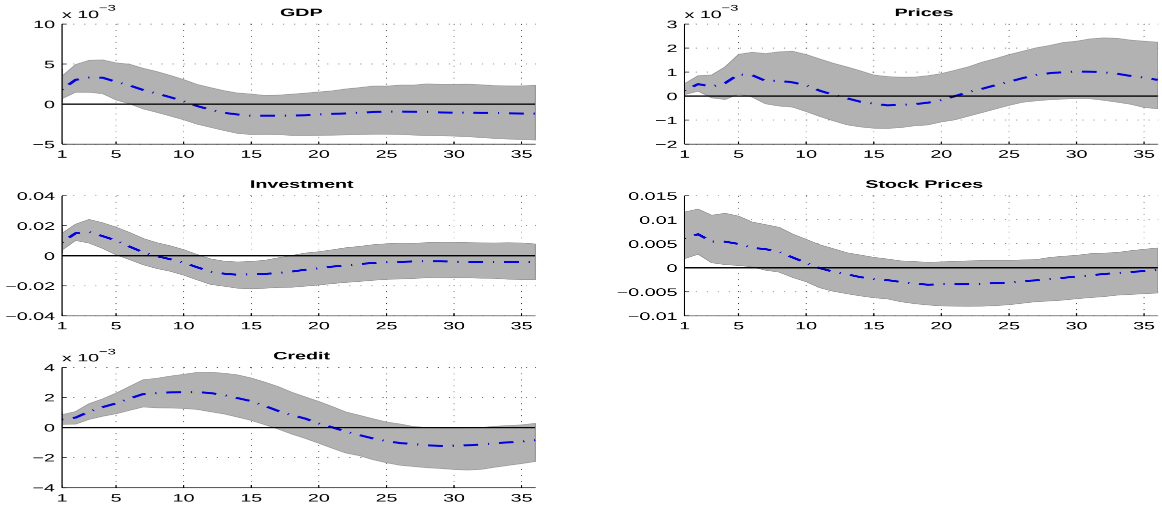

Figure 19: Median impulse responses to an one-standard-deviation risk shock for the model including risk and net-worth shocks.

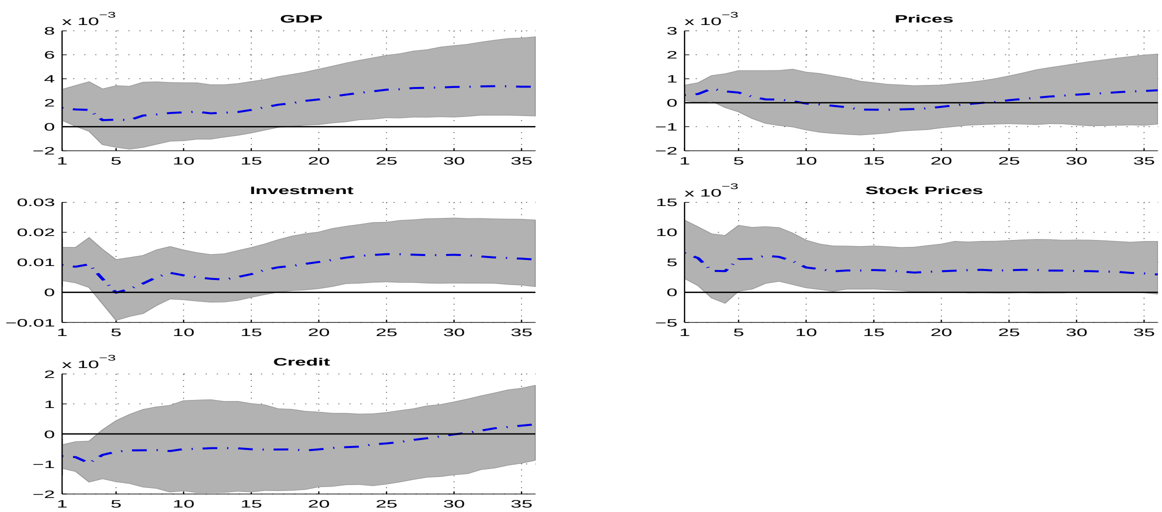

Figure 20: Median impulse responses to an one-standard-deviation net-worth shock for the model including risk and net-worth shocks.