Monetary Policy Shocks and Financial Conditions: A Monte Carlo Experiment

Efrem Castelnuovo*
University of Padova

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Abstract

The effects of monetary policy shocks on financial conditions are often estimated by appealing to recursive Vector AutoRegressions (VARs). We assess the ability of this class of VARs to recover the true effects of a monetary policy shock via a Monte Carlo experiment in which the Data Generating Process is a Dynamic Stochastic General Equilibrium (DSGE) model featuring macro-finance interactions and estimated with U.S. quarterly data. Our DSGE model predicts a negative and significant reaction of financial conditions to an unexpected monetary policy tightening. We show that such reaction is just overlooked by recursive VARs.

JEL classification: E32, E44.

Keywords: Kansas City Financial Stress Index, financial-macroeconomic interactions in a DSGE model, monetary policy shock, Cholesky-VARs, MonteCarlo exercises.

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1 Introduction

The recent financial crisis has re-boosted the discussion on how central banks should deal with financial markets' swings. Critically, this depends on the ability to influence financial markets by monetary policy makers. The impact of monetary policy shocks on financial markets has often been assessed with the use of Vector AutoRegressions (VARs).[1] Typically, monetary policy shocks have been identified by appealing to 'recursive VARs'. In short, a Cholesky decomposition of the variance-covariance matrix of the residuals is performed in VARs in which the policy rate is ordered after 'slow moving variables', which react to monetary policy shocks with a one-period delay. This assumption is handy, in that it does not force the researcher to identify other shocks than the monetary policy shock (Christiano, Eichenbaum, and Evans (1999)). However, a Cholesky-based identification of the monetary policy shock does not line up with conventional wisdom, which suggests an immediate reaction of asset prices to a monetary policy shock (see Bjørnland and Leitemo (2008) and the references therein for discussions).

This paper asks the following question:

> *Suppose a DSGE model allowing for* contemporaneous *macro-finance interactions is the Data Generating Process of the economy. Is a Cholesky-VAR able to recover the true response of financial conditions to a monetary policy shock?*

We investigate this issue by proceeding in two steps. Firstly, we estimate a DSGE model featuring simultaneous interactions between the financial and real sides of the economy with U.S. data. We concentrate on the framework developed by Nisticò (2007), Airaudo, Nisticò, and Zanna (2008), and Castelnuovo and Nisticò (2010), in which households' consumption decisions are taken conditional on a finite (in expected terms) financial planning horizon. Consequently, fluctuations in households' financial wealth influence individual and aggregate consumption and, therefore, aggregate demand.[2] Given that swings in financial conditions may affect the business cycle, monetary policy interventions to dampen fluctuations in the financial markets may very well occur. Our

[1] A non-exaustive list includes Lee (1992), Thorbecke (1997), Patelis (1997), Millard and Wells (2003), Neri (2004).

[2] Nisticò (2007, 2010) analyzes optimal monetary policy with a calibrated purely forward looking version of the model we employ in our investigation. Airaudo, Nisticò, and Zanna (2008) deal with the issue of equilibrium uniqueness and stability under learning with the set up proposed by Nisticò (2007).

empirical model is flexible enough to allow (and test) for this scenario to occur. As empirical proxy for the U.S. financial conditions, we employ the Kansas City Financial Stress Index (KCFSI) recently developed by Hakkio and Keeton (2009). Such index is computed as the common factor of a variety of financial indexes continuously monitored by policymakers and financial analysts (we postpone the description of the KCFSI to the following Section). To our knowledge, this is the first contribution employing a financial conditions index to estimate a structural DSGE model for the U.S. economy.

This first step is instrumental to the second one, in which we employ the estimated DSGE model as Data Generating Process (DGP) in our Monte Carlo exercise. Such exercise i) simulates artificial data, and ii) employ them to estimate impulse responses to a monetary policy shock identified with a Cholesky-VAR. We then contrast the (true) DSGE model-consistent impulse response functions with those produced with Cholesky-VARs. This comparison allows us to assess to what extent the imposition of the (wrong) Cholesky timing is problematic.

We find evidence in favor of structural macro-finance interactions in our DSGE model.[3] Consistently, conditional on our estimated DSGE model, impulse responses to a monetary policy shock put in evidence the existence of strong macro-finance interactions in the U.S. economy. However, our Monte Carlo exercises reveal that such interactions are in fact overlooked by Cholesky-VARs, which substantially underestimate the reaction of financial conditions to a monetary policy shock. This is due to the imposition of (wrong) zero restrictions on the matrix regulating the contemporaneous relationships among the modeled variables, which force all variables ordered before the policy rate to react with a lag. This timing is inconsistent with our DSGE model, which in our Monte Carlo experiment is the DGP. As a consequence, the Cholesky-VAR monetary policy 'shock' is, in fact, a linear combination of the structural shocks modeled with our DSGE model. These structural shocks exert (partly) offsetting effects on financial conditions. Hence, their combination leads to a milder reaction of financial conditions than the one actually realizing in reaction to the structural monetary policy shock only.

To summarize, a muted reaction of financial conditions to a monetary policy shock identified with a Cholesky-VAR is consistent with a 'significant' impact of monetary

[3]This result, obtained with the KCFSI as observable variable in the estimation, corroborates the findings in Castelnuovo and Nisticò (2010), who work with the S&P500 index. The empirical support for an active financial wealth effect is relevant in light of the policy prescriptions conditional on an active financial wealth effect recently proposed by Nisticò (2007), Airaudo, Nisticò, and Zanna (2008), and Nisticò (2010).

policy shocks on financial conditions under the true data generating process. Therefore, our results cast doubts on the recursive scheme as suited to identify the effects of a monetary policy shock on financial conditions, therefore calling for the employment of alternative identification schemes allowing for contemporaneous interactions between the financial and the real sides of the economy, such as non-recursive short-run restrictions as in Leeper and Roush (2003) and Poilly (2010), the mixture of short- and long-run restrictions (Bjørnland and Leitemo (2008)), and 'sign restrictions' (see Canova and Paustian (2010) and the references therein).

The paper is structured as follows. Section 2 presents our new-Keynesian framework of the business cycle in which financial conditions are allowed, but not required, to affect the equilibrium values of output, inflation, and the policy rate. Section 3 presents the estimates of our DSGE model, which we use as our DGP in the following Section. Section 4 conducts Monte Carlo exercises to assess the ability of a Cholesky-VAR model to recover the 'true' macro-finance interactions as proposed by our estimated DSGE framework, and offers an interpretation to our main result. Section 5 discusses some related literature. Section 6 concludes.

2 Modeling the U.S. macro-finance interactions: A DSGE framework

We model the U.S. macro-finance interactions with the DSGE framework recently proposed by Castelnuovo and Nisticò (2010):[4]

$$
\begin{aligned}
\pi_t &= \beta(1+\alpha\beta)^{-1}E_t\pi_{t+1} + \alpha(1+\alpha\beta)^{-1}\pi_{t-1} + \kappa x_t + \varepsilon_t^{\pi}, && (1)\\
x_t &= w_x E_t x_{t+1} + (1-w_x)x_{t-1} - \delta_x(R_t - E_t\pi_{t+1}) + \psi s_t + \varepsilon_t^{x} && (2)\\
s_t &= \beta E_t s_{t+1} + \lambda E_t x_{t+1} - \delta_s(R_t - E_t\pi_{t+1}) + \varepsilon_t^{s} && (3)\\
R_t &= \phi_R R_{t-1} + (1-\phi_R)(\phi_\pi \pi_t + \phi_x x_t + \phi_s s_t) + \varepsilon_t^{R}, && (4)\\
\varepsilon_t^{j} &= \rho_x \varepsilon_{t-1}^{j} + \eta_t^{j}, && (5)\\
\eta_t^{j} &\sim i.i.d.N(0,\sigma_j^2), j \in \{\pi, x, s, R\}\,. && (6)
\end{aligned}
$$

Eq. (1) is an expectational new-Keynesian Phillips curve (NKPC) in which π_t stands for the inflation rate, β identifies the discount factor, α captures indexation to past-

[4] Details on the microfoundation of this model are provided in Castelnuovo and Nisticò (2010).

inflation, x_t identifies the output gap, whose impact on current inflation is influenced by the slope-parameter κ, and ε_t^{π} is interpreted as 'inflation' shock, or 'supply' shifter.[5]

Eq. (2) is obtained by log-linearizing the consumption Euler equation stemming from households' intertemporal problem. Output fluctuations are driven by both expectations on future realizations of the output gap and by its past realizations, with w_x being the weight assigned to expectations, and $1-w_x$ to past output. The intertemporal substitution decisions are influenced by the ex-ante real interest rate, whose loading is δ_x. The demand shock ε_t^x may be interpreted as a households' preference shock, or a fiscal shock. With respect to the standard IS curve, our eq. (2) embeds the 'financial conditions' indicator s_t. This indicator takes high (low) values when the financial conditions are good (bad). Therefore, if ψ is strictly positive, a high (low) realization of s_t leads to output booms (busts) due to more (less) sound financial conditions, e.g. easier (more difficult) access to credit markets, low perceived risk, and the like. The presence of s_t in the IS schedule is based on households having a positive probability ϑ of exiting the financial market each period, with $\vartheta \in [0,1], \psi(\vartheta) \geq 0, \psi(0) = 0, \psi' > 0$. The law of motion of the financial soundness s_t is given by eq. (3). Solving it forward, the link between current realizations of the financial soundness and future, expected realizations of the output gap, the real interest rate, and the stochastic component ε_t^s (which may be interpreted as 'non-fundamental' component or time-varying 'risk premium' as in Castelnuovo and Nisticò (2010)) emerges.

Eq. (4) is a Taylor rule postulating the systematic reaction of the policy rate to movements in the inflation gap and the output gap. Past policy decisions matter, and their impact is captured by the interest rate smoothing parameter ϕ_R. The random shock ε_t^R stands for the monetary policy shock. With respect to the standard Taylor rule as modeled by e.g. Clarida, Galí, and Gertler (2000), we consider an augmented version possibly embedding the financial soundness indicator s_t, whose loading is ϕ_s. This is another channel through which financial conditions may matter, in that a positive (stabilizing) monetary policy reaction to such indicator calls for movements in the policy rate and, consequently, output and inflation.

The autoregressive shocks (5) and the mutually and temporally uncorrelated innovation processes (6) close the model. Under the constraints $\psi = \phi_s = 0$, this model boils down to the standard AD/AS framework successfully employed in empirical work

[5] We abstain from modeling a 'cost-channel' transmission mechanism, which has been shown to be of mild importance at best as for the empirical fit of small-scale models like the one employed in this paper - see Castelnuovo (2011).

on the U.S. macroeconomic dynamics by a variety of authors (among others, Lubik and Schorfheide (2004), Boivin and Giannoni (2006b), Benati (2008), Benati and Surico (2008), Benati and Surico (2009), Canova (2009)). The employment of a small-scale model makes it easier to control for all the sources of discrepancy between our DSGE and the Cholesky-VAR impulse responses. An analysis with a larger-scale model like the ones in Smets and Wouters (2007) or Justiniano and Primiceri (2008) is left to future research.

3 Empirical analysis

We estimate the model (1)-(6) with Bayesian methods (see An and Schorfheide (2007), Canova and Sala (2009), Fernández-Villaverde (2010)).

3.1 The data

We focus on the sample 1990:I-2008:II, U.S. quarterly data. The reason for our sample choice is threefold. Firstly, data availability (the KCFSI's first observation is February 1990). Secondly, we aim at analyzing a stable policy conduct. Therefore, we restrict the sample to the Greenspan-Bernanke regime to avoid dealing with the policy break occurred with the advent of Paul Volcker at the chairmanship of the FOMC,[6] which may have importantly shaped the interactions and dynamics of the U.S. macroeconomic variables (Castelnuovo (2010b), Castelnuovo and Surico (2010)) and the impact of systematic monetary policy moves on inflation expectations (Castelnuovo (2010c)). Finally, the end of the sample is chosen to avoid dealing with the acceleration of the financial crises began with the bankruptcy of Lehman Brothers in September 2008, which triggered non-standard policy moves by the Fed (Brunnermeier (2009)).

We employ four observables. The output gap is computed as log-deviation of the real GDP with respect to the potential output level estimated by the Congressional Budget Office. The inflation rate is the growth rate of the GDP deflator. The empirical proxy for the short-term nominal interest rate is the effective federal funds rate (average of monthly values). All these series are demeaned prior to estimation.

[6] A non exhaustive list of contributions supporting this break includes Clarida, Galí, and Gertler (2000), Lubik and Schorfheide (2004), Boivin and Giannoni (2006b), Canova (2009), Benati and Surico (2009), Mavroeidis (2010), and Inoue and Rossi (2011). For a critical view on the presence and relevance of this break, see Sims and Zha (2006), Justiniano and Primiceri (2008), and Canova and Gambetti (2010).

The choice of the empirical counterpart for the stock price gap is clearly open to discussion. From a theoretical standpoint, this measure should be related to the impact that financial wealth fluctuations exert on households' consumption decisions. As anticipated, we use the Kansas City Financial Condition Index recently elaborated by Hakkio and Keeton (2009). Importantly, they stress that

> "An increase in financial stress can lead to a decline in economic activity [...]. [Section I noted that] financial stress is associated with two kinds of uncertainty-uncertainty about the fundamental value of assets and uncertainty about the behavior of other investors. Both kinds of uncertainty lead to increased volatility in asset prices. [...] The volatility may also cause households to cut back on spending, as they become more uncertain about their future wealth." (Hakkio and Keeton, 2009, p. 29).[7]

The source of our data is the Federal Reserve Bank of St. Louis (FREDII), with the exception of the KCFSI, which is downloaded from the Federal Reserve Bank of Kansas' website.

3.2 Posterior densities

The posterior estimates of our 'DSGE model with financial soundness' are reported in Table 1 (first column).[8] A wealth of considerations can be made. Firstly, the data support the presence of financial wealth (as proxied by the KCFSI) in the IS schedule. The posterior mean of the parameter ψ is 0.17, with a 90% credible set equal to [0.07,0.27]. Formal support comes from the posterior odds. Our model's (log) marginal likelihood is -15.02. The model estimated under the constraint $\psi = 0$ returns a marginal likelihood equal to -19.58, which suggests a deterioration in the model fit. Given an a-priori uniform distribution over the two models, this difference translates in a posterior odds ratio equal to $exp(-19.58 + 15.02) = 0.0105$. Therefore, our marginal likelihoods clearly favor a parameterization consistent with the presence of a measure of financial soundness in the IS schedule, a finding in line with Castelnuovo and Nisticò (2010). The sign of the posterior mean is in line with economic intuition: the higher the financial soundness, the higher households' incentive to allocate resources to current consumption, the better the economic conditions as captured by the output gap.

[7] The KCFSI is a composite indicator collecting information coming from a variety of financial indexes - see Hakkio and Keeton (2009) for details. We propose further considerations on this index in our Appendix.

[8] We discuss details on our econometric exercise in our Appendix.

The 'Standard NK model' estimated under the constraints $\psi = \phi_s = 0$ proves to fit the data worse than our 'model with financial soundness'. The (log) marginal likelihood of the model without financial indicators read -28.96, a figure remarkably lower than that associated to the model with financial soundness. The Kass and Raftery (1995) statistic $KR = 2[-15.02 - (-28.96)] \approx 27.90$. According to Kass and Raftery (1995), a KR statistic larger than 10 suggests a 'very strong' evidence in favor of the model with the higher log-marginal likelihood. These constraints lead to some adjustments by the common parameters. As for the estimates of the parameters of the constrained model, the weight of the forward looking output in the IS schedule is higher; the loading of the real ex ante interest rate in the stock price equation is lower; the reaction of inflation by the FOMC is slightly higher.

Secondly, the Fed is found to have had concerns over financial conditions. The 90% credible set associated to ϕ_s is [0.74,1.56], with a posterior mean equal to 1.15. Forcing the model to lower realizations of the ϕ_s parameter leads to a clear worsening of its marginal likelihood.[9] Again, this finding is in line with Castelnuovo and Nisticò (2010). Clearly, the Federal Reserve has monitored measures of financial stress during the 1990-2008 period. Given the 'demand push' possibly due to variations in the stock of financial wealth, such a reaction could be rationalized with the Federal Reserve's aim to stabilize the business cycle and inflation (and, possibly, the financial markets). Rigobon and Sack (2003) estimate the Fed's reaction to movements in the stock prices with an econometric strategy tackling endogeneity issues via heteroskedasticity, and find a significant reaction during the Great Moderation. D'Agostino, Sala, and Surico (2005) find evidence in favor of a systematic policy reaction to stock prices in phases of high volatility of the stock market. Furlanetto (2011) applies Rigobon and Sack's to a variety of countries and longer samples. As for the U.S., he finds a substantial reduction in the policy reaction to stock prices at the end of the 1990s, possibly due to a 'substitution effect' leading to a higher response to real estate prices.[10]

[9] The model estimated under the constraint $\phi_s = 0.1$ is associated to a log-marginal likelihood equal to -23.48. In this constrained version of the model, the posterior mode of ϕ_π adjusts upward and takes the value $\phi_\pi = 1.81$. This is due to the condition for uniqueness of the rational expectations equilibrium in this model, which is non-standard due to the presence of the financial wealth-effect in the IS schedule. For in-depth investigations, see Nisticò (2007) and Airaudo, Nisticò, and Zanna (2008).

[10] One has to interprest this result with care. This evidence is also consistent with the Federal Reserve considering financial indexes as leading indicators possibly embedding relevant information to predict future output and inflation. In the attempt to distinguishing the FOMC's reaction to forecasts of traditional goal variables from the FOMC's independent reaction to changes in equity prices, Fuhrer and Tootell (2008) employ the Greenbook forecasts examined by the FOMC before each

Thirdly, the remaining parameters take reasonable values, mostly in line with the current literature. In particular, we find a low degree of price indexation; a hybrid IS curve, whose rationale may be found in habit formation; a strong, systematic policy reaction to inflation; a high degree of interest rate smoothing. Interestingly, the autoregressive parameters for the stochastic processes ('shocks') take values lower than 0.90, an evidence which suggests that the model features an internal propagation mechanism able to capture our observables' persistence.

We use this estimated DSGE model as our DGP in the Monte Carlo exercise conducted in the following Section.

4 What is the effect of a monetary policy shock on the financial conditions? Contrasting DSGE and VAR models

4.1 The DSGE evidence

How do financial conditions react to a monetary policy shock? To answer this question,

1a) we sample a set of values for the vector $\boldsymbol{\xi}$ from the posterior density $p(\boldsymbol{\xi} \mid \{\mathbf{Y}_t\}_{t=1}^{T})$;

2a) we compute the impulse responses of our endogenous variables, conditional on our DSGE model calibrated with the sampled set of values for $\boldsymbol{\xi}$, to an unexpected 25 basis points hike;

3a) we repeat steps 1a) and 2a) 5,000 times;

4a) we plot the mean reactions along with the $[5th, 95th]$ percentiles.

Figure 1 (left column) plots the Bayesian impulse responses to an unexpected 25 basis points hike. Such responses points to the following facts:

a) *the reaction of the financial conditions is negative, persistent, and significant.*[11] The financial conditions react negatively and significantly to an unexpected monetary policy tightening. This result, obtained with quarterly data, echoes the

policy decision. They find little evidence to support the proposition that the FOMC responds to stock values *per se*. Our results are also consistent with the 'instrumental' interpretation of the stock prices being statistically significant in estimated policy rules for the United States. We then refrain from stating that our evidence points towards the financial stress as a monetary policy 'goal'.

[11] A reaction at quarter j is termed 'significant' if the zero value does not belong to the set identified by the [5th,95th] percentiles of the distribution of the impulse response function of interest at quarter j.

finding by Rigobon and Sack (2004) obtained with daily data. The financial markets take four quarters to go back to steady state. The deepest 'financial crises' conditional on a monetary policy shock occurs on impact, a finding in line with Castelnuovo and Nisticò (2010) and Bjørnland and Leitemo (2008);[12]

b) *the reaction of output is negative, persistent, and significant.* The reaction takes almost four years to go back to its steady state value following a hump-shaped path as in Furher (2000);

c) *the reaction of inflation is negative, persistent, and significant.* Inflation takes three years to return to zero. The reaction is not hump-shaped due to the very low degree of price indexation in this sample;

d) *the reaction of the policy rate is positive, persistent, and significant.*[13]

4.2 The Cholesky-VAR evidence: A Monte Carlo experiment

We now ask the question presented in our Introduction:

Assume our DSGE model to be the Data Generating Process. Is a Cholesky-VAR able to recover the true response of financial conditions to a monetary policy shock?

To answer this question, we set up a Monte Carlo experiment. We implement the following steps:

1b) we sample a set of values for the vector $\boldsymbol{\xi}$ from the posterior density $p(\boldsymbol{\xi} \mid \{\mathbf{Y}_t\}_{t=1}^{T})$, and produce pseudo data for our endogenous variables of $T = 74$ (comparable to the sample 1990:I-2008:II) by employing our DSGE model (conditional on the sampled parameterization for the vector $\boldsymbol{\xi}$) as DGP;

[12] Bjørnland and Leitemo (2008) employ monthly data in their analysis. They find the through of the response of stock prices to take place during the first few months after the shock. We read their evidence as pointing toward the quarter after the shock as being the one capturing the deepest point of the 'financial recession' caused by a monetary policy shock.

[13] In conducting our exercise, we assume that a single regime has occurred during the period under scrutiny. Davig and Hakkio (2010) estimate a bivariate VAR modeling a business cycle indicator and the KCFSI. They allow for two regimes to take place. Interestingly, they find that i) in the 'normal' regime, financial stress is high, economic activity is low, an volatility is low, whereas in the 'distressed' regime, financial stress is high, economic activity is low, and volatility is high; ii) a shock to financial stress is found to have a larger, and longer lasting negative effect on economic activity when the economy is in the 'distressed' regime; iii) an increase in financial stress increases the probability that the economy will shift from the 'normal' regime to the 'distressed' regime. Again, our impulse response functions should be interpreted as an average response between the 'normal' and the 'distressed' regimes.

2b) we compute the responses of our endogenous variables to an unexpected 25 basis points hike by estimating a Cholesky-VAR (ordering: Output, inflation, financial conditions, and the policy rate as last variable) with the pseudo data produced at point 1b);

3b) we repeat steps 1b) and 2b) 5,000 times;

4b) we plot the mean reactions along with the $[5th, 95th]$ percentiles.

Figure 1 (right column) plots the responses obtained in our controlled, in-lab exercise. These reactions hardly replicate the facts identified with our structural model. First and foremost, fact a) is completely missed. *According to standard Cholesky-VARs, monetary policy shocks just do not affect financial conditions.* The mean reaction is clearly flat. The selected [5th,95th] percentiles just contain the zero line for all the quarters we focus on. Given that the 'truth', i.e. the reaction of our financial indicator to a monetary policy shock suggested by our DSGE model, is dramatically different, this result is intriguing. As anticipated, most authors have identified a monetary policy shock by appealing to a Cholesky (recursive) factorization of the variance-covariance matrix of the reduced-form VAR residuals. These contributions have typically found quite mild, and often insignificant, reactions of the financial indicators to a monetary policy shock (Lee (1992), Thorbecke (1997), Patelis (1997), Millard and Wells (2003), Neri (2004)). Our Monte Carlo experiment proves that *evidence of a flat reaction of a financial indicator to a Cholesky-VAR monetary policy shocks is fully compatible with a truly 'significant' reaction of the financial markets to such a shock.*

Facts b) and c) are also hardly replicated. Our Cholesky-VARs suggest a negative reaction of output and inflation *on average*. However, such reactions are quite imprecisely estimated, and hardly significant. In particular, the reaction of output turns out to be substantially underestimated. This is in line with some recent empirical findings by Castelnuovo (2010a), who show that Cholesky-VARs may dramatically underestimate the real effects of a monetary policy shock in a standard new-Keynesian framework in which financial conditions are redundant.

Differently, fact d) is well captured by our Cholesky-VARs, i.e. the pattern of the policy rate in response to a monetary policy shock is well captured by Cholesky-VARs.

We interpret the failure of Cholesky-VARs to correctly recover the true effects of a monetary policy shock on financial conditions as follows. The imposition of (wrong) zero restrictions on the matrix regulating the contemporaneous relationships among the modeled variables forces all variables ordered before the policy rate to react with a lag. This timing is inconsistent with our DSGE model, which in our Monte Carlo experiment is the DGP. As a consequence, the Cholesky-VAR monetary policy 'shock' is, in fact, a linear combination of the structural shocks modeled with our DSGE model.[14] Then, if two structural shocks exert effects on financial conditions with similar magnitude but different sign, the response of financial conditions to a monetary policy shock will look flat. It is easy to think of combinations of structural shocks leading to this outcome. For instance, a monetary policy tightening leads to a phase of financial stress in the short run. On the contrary, a positive shock to financial conditions opens a positive stock market gap. These two shocks may very well enter the linear combination that composes the Cholesky-VAR shock, therefore falsely suggesting a zero reaction to a monetary policy innovation.

Importantly, our evidence is robust to a variety of checks including i) the imposition of the DSGE consistent $\boldsymbol{A}(L)$ matrices in our estimated Cholesky-VARs; ii) population (as opposed to sample) impulse response functions; iii) optimally selected lags for our Cholesky-VARs (selection based on the Schwarz criterion); iv) the estimation of our DSGE model allowing for measurement errors; v) an upper triangular (as opposed to the standard lower triangular) Cholesky matrix. These robustness checks are discusses in our Appendix for brevity.

5 Related contributions

Before concluding, we note connections with some related contributions. Some recent research has shown that the Cholesky-VAR scheme is quite bias-prone if the timing of the transmission mechanism of the true DGP is inconsistent with the restrictions imposed by a recursive scheme (Canova and Pina (2005), Bjørnland and Leitemo (2008), Carlstrom, Fuerst, and Paustian (2009), Castelnuovo (2010a)). Surprisingly, however, little is known on the consequences of a wrong identification scheme as for the macro-finance interactions. Bjørnland and Leitemo (2008) show with actual U.S. data that Cholesky-VARs tend to return a counter-intuitive long-run positive reaction of the stock market to a monetary policy shock. Differently, a novel mix of short and long run restrictions deliver more reasonable reactions. A related paper is Poilly (2010), who investigates the consequences of estimating a medium-scale DSGE framework featuring complementarity in consumption and real-balances with indirect inference based on

[14]Our Appendix provides details on this issue.

impulse response matching. She shows that the estimated structural parameters are sensitive to the VAR identification scheme. In particular, a real balance effect is unveiled by the non-recursive VAR. With respect to these last two papers, our exercise is based on Monte Carlo simulations. Therefore, we are able to control for all the possible sources of distortions of our Cholesky-VAR responses and identify the timing discrepancy between DSGE and Cholesky-VARs as the true problematic element causing such distortions.

In conducting our Monte Carlo experiment, we employ an estimated DSGE model for the U.S. economy featuring macro-finance interactions. Structural DSGE models allowing for macro-finance interactions have been estimated by Milani (2008), Castelnuovo and Nisticò (2010), and Christiano, Motto, and Rostagno (2010). These contributions employ the S&P500 index to capture asset prices' behavior. Differently, in our empirical exercise we consider a composite indicator, i.e. the 'Kansas City Financial Stress Indicator' (KCFSI hereafter) recently developed by Hakkio and Keeton (2009). To our knowledge, this is the first contribution exploiting the KCFSI, and a financial conditions index in general, as an observable to estimate a DSGE model embedding a financial channel for the U.S. economy.

Challe and Giannitsarou (2010) build up a model in which stocks are priced consistently with households' optimization problem but do not exert any impact on consumption. They aim to show that a calibrated DSGE model is able to replicate the reaction of stock prices to a monetary policy shock as estimated by some VAR analysis. With respect to Challe and Giannitsarou (2010), we allow for a two-way interaction between the real and the financial part of the system, and we estimate our framework with U.S. data instead of resorting to calibration.

A related literature (Queijo von Heideken (2009), Gerali, Neri, Sessa, and Signoretti (2009), Christiano, Motto, and Rostagno (2010)) investigates the importance of the banking sector/financial frictions by working with extensions of the Bernanke, Gertler, and Gilchrist (1999) financial-accelerator model. Our approach complements these investigations by scrutinizing the impact of financial fluctuations in a model in which movements in the financial wealth affect households' decisions.

6 Conclusions

We estimated a DSGE model allowing for macro-financial interactions in the U.S. economy, 1990Q1-2008Q2. According to our estimated DSGE framework, monetary policy shocks exert a significant effect on financial conditions. A Monte Carlo experiment, however, reveals that such effect is completely overlooked by VARs in which the monetary policy shock is identified via the commonly employed Cholesky-restrictions on the contemporaneous relationships among the modeled variables. We then conclude that the mild reaction of financial conditions to a monetary policy shock, a result often found when working with Cholesky-VARs, is fully consistent with monetary policy shocks effectively causing financial cycles. In other words, mild financial reactions in Cholesky-VARs may be artifact due to wrong identifying restrictions, more than true facts.

Our results call for the employment of alternative identification schemes admitting simultaneous macro-finance interactions in response to a monetary policy shock. One option is to work with simultaneous short-run interactions between interest rates and financial (monetary) indicators as in Leeper and Roush (2003) and Poilly (2010). A second option is to allow for a mixture of short- and long-run restrictions to identify the monetary policy shock and its effects on the financial markets. A recent application of this strategy is offered by Bjørnland and Leitemo (2008). A third possible strategy is to work with sets of 'sign restrictions' suggested by theoretical model and/or conventional wisdom. In a recent paper, Canova and Paustian (2010) discuss the mapping between VAR sign restrictions and structural models at length. We plan to assess the ability of these strategies to identify the macro-finance interactions triggered by a monetary policy shock with future research.

Appendix

A1 Interpretation of the Cholesky-VAR evidence: Some matrix algebra

The zero-restrictions imposed by Cholesky-VARs are inconsistent with those imposed by a large variety of DSGE models (included the one in this paper). It is easy to show that the (rational expectations) solution of a model like (1)-(6) has a VAR(2) representation, which reads:[15]

[15] Fernández-Villaverde and Rubio-Ramírez (2006) and Fernández-Villaverde, Rubio-Ramírez, Sargent, and Watson (2007) derive a necessary condition to ensure the existence of the VAR representation of a DSGE model (i.e. to check if the DSGE model is 'invertible'), which is clearly satisfied here.

$$\begin{bmatrix} x_t \\ \pi_t \\ s_t \\ R_t \end{bmatrix} = \underset{[4x4]}{\boldsymbol{A}_1} \begin{bmatrix} x_{t-1} \\ \pi_{t-1} \\ s_{t-1} \\ R_{t-1} \end{bmatrix} + \underset{[4x4]}{\boldsymbol{A}_2} \begin{bmatrix} x_{t-2} \\ \pi_{t-2} \\ s_{t-2} \\ R_{t-2} \end{bmatrix} + \underset{[4x4]}{\boldsymbol{B}} \begin{bmatrix} \eta_t^x \\ \eta_t^\pi \\ \eta_t^s \\ \eta_t^R \end{bmatrix} \tag{7}$$

Notice, in particular, that the 'impulse' matrix $\boldsymbol{B}$ is full, i.e. all elements of that matrix are non-zero, which implies that each shock $\eta_t^j, j = \{x, \pi, s, R\}$ can immediately affect each variable of the vector $\boldsymbol{z}_t$.

The variance-covariance matrix of $\boldsymbol{B\eta_t}$ is given by $\boldsymbol{B\Omega B}^T$, where $\boldsymbol{\Omega}$ is a diagonal matrix of full rank four with the variances of the shocks positioned on the main diagonal. Without loss of generality for the point we aim at making, and just for the sake of simplicity, we set $\boldsymbol{\Omega} = \boldsymbol{I}_4$.

Of course, when conducting an econometric exercise, the fundamental shocks $\boldsymbol{\eta}_t$ are not observable, and must be inferred. To do so, the econometrician can estimate a reduced form VAR(2)

$$\begin{bmatrix} x_t \\ \pi_t \\ s_t \\ R_t \end{bmatrix} = \boldsymbol{A}_1 \begin{bmatrix} x_{t-1} \\ \pi_{t-1} \\ s_{t-1} \\ R_{t-1} \end{bmatrix} + \boldsymbol{A}_2 \begin{bmatrix} x_{t-2} \\ \pi_{t-2} \\ s_{t-2} \\ R_{t-2} \end{bmatrix} + \begin{bmatrix} \zeta_t^x \\ \zeta_t^\pi \\ \zeta_t^s \\ \zeta_t^R \end{bmatrix}, \tag{8}$$

where $\boldsymbol{\zeta}_t$ is a vector of *residuals* whose variance-covariance $VCV(\boldsymbol{\zeta}) = \boldsymbol{\Lambda}$ is a full (non diagonal) $[4x4]$ matrix.

As commented above, to recover the unobserved structural monetary policy shock η_t^R, researchers often impose a Cholesky structure to the system, which assumes delayed effects of the 'monetary policy shock' on the variables located before the nominal interest rate in the vector $\boldsymbol{z}_t$. This is done by computing the unique *lower triangular* matrix $\widetilde{\boldsymbol{B}}$ such that

$$\widetilde{\boldsymbol{B}}\boldsymbol{\varphi_t} = \boldsymbol{\zeta_t}, \text{ with } \boldsymbol{\varphi_t} = [\varphi_t^x, \varphi_t^\pi, \varphi_t^s, \varphi_t^R]^T.$$

The Cholesky 'shocks' $\boldsymbol{\varphi_t}$, which are orthogonal and are assumed to have unitary variance, are then identified by computing the elements of the matrix $\widetilde{\boldsymbol{B}}$ such that

$$\widetilde{\boldsymbol{B}}\widetilde{\boldsymbol{B}}^T = \boldsymbol{\Lambda}.$$

This implies that the equivalence $\widetilde{\boldsymbol{B}}\widetilde{\boldsymbol{B}}^T = \boldsymbol{BB}^T$ must hold true, which allows us to recover the elements in $\widetilde{\boldsymbol{B}}$ as a function of the (convolutions of) structural parameters in $\boldsymbol{B}$. Hence, given the restrictions

$$\widetilde{\boldsymbol{B}}\boldsymbol{\varphi}_t = \boldsymbol{B}\boldsymbol{\eta}_t$$

imposed by eqs. (7) and (8), one may express the Cholesky 'shocks' $\boldsymbol{\varphi_t}$ in terms of the DSGE shocks $\boldsymbol{\eta}_t$ as

$$\boldsymbol{\varphi}_t = \Phi\boldsymbol{\eta}_t,$$

with $\Phi \equiv \widetilde{\boldsymbol{B}}^{-1}\widetilde{\boldsymbol{B}} = \begin{bmatrix} \phi_{11} & \cdots & \phi_{14} \\ \vdots & \ddots & \vdots \\ \phi_{41} & \cdots & \phi_{44} \end{bmatrix}$. Therefore, the mapping linking the Cholesky-VAR reduced form 'shock' φ_t^R and the structural shocks η_t^j is[16]

$$\varphi_t^R = \phi_{41}\eta_t^x + \phi_{42}\eta_t^\pi + \phi_{43}\eta_t^s + \phi_{44}\eta_t^R. \tag{9}$$

Clearly, the only case in which Cholesky might get the effects of the monetary policy shock η_t^R right is that represented by $\phi_{41} = \phi_{42} = \phi_{43} = 0$ and $\phi_{44} \neq 0$. However, the constraints $\phi_{41} = \phi_{42} = \phi_{43} = 0$ are just inconsistent with the timing-structure of our DSGE model (1)-(6). Therefore, we can actually get distorted responses under the Cholesky restrictions. Our computations suggest that the two structural shocks contributing the most to the volatility of φ_t^R are the monetary policy shock η_t^R, whose distribution features [5th,95th] percentiles equal to [64%,97%], and the financial shock η_t^s, whose participation reaches 28% (95th percentile). The remaining shocks offer a much milder contribution.

We are then able to interpret the outcome of our Monte Carlo exercise. A truly structural monetary policy shock (say, an unexpected interest rate hike) causes a temporary financial stress (a decline of the financial conditions index), a real recession, and a deflationary phase. Viceversa, a positive financial shock (say, an unexpected improvement in financial conditions) leads to better financial conditions, an output expansion, and an inflationary phase. The combination of these two shocks (partly) offset the effects on the financial and macroeconomic variables. In contrast, this combination leads to unambiguous effects as for the policy rate.

A2 Robustness checks

We deal with robustness checks along different dimensions.

[16] For a step-by-step derivation of this mapping in the context of a standard AD-AS microfounded DGSE model of the business cycle, see the Technical Appendix provided by Carlstrom, Fuerst, and Paustian (2009).

- *DSGE model consistent $\boldsymbol{A}(L)$ matrices.* One driver of the discrepancies we found between the DSGE and the Cholesky-VARs' impulse responses is theoretically the different coefficients in the $\boldsymbol{A}_1$ and $\boldsymbol{A}_2$ matrices. If, for whatever reason (say, e.g. small sample biases), Cholesky-VARs are not able to recover the correct coefficients of the lagged structure of the VAR, their impulse responses may be affected. We then imposed $\boldsymbol{A}_1$ and $\boldsymbol{A}_2$ to our estimated VARs in our Monte Carlo experiment. Figure 2 displays the impulse responses related to this robustness check.

- *Population moments.* Of course, the small sample bias issue may affect the ability of Cholesky-VARs to recover the true effects of a monetary policy shock. To assess the relevance of this issue we computed populations moments by endowing the econometrician with samples with $T = 100,000$. Figure 3 depicts the impulse responses related to this robustness check.

- *Optimal selection of the number of lags of the VARs.* Given that the DSGE model has a finite VAR(2) representation, our VARs are estimated with two lags. Of course, sample uncertainty may call for a different number of lags for some draws of the artificial data. We then re-run our exercise by optimally selecting, per each estimated VAR, the number of lags according to the Schwarz information criterion. Figure 4 depicts the results of this robustness check.

- *Measurement errors in the estimation of the DSGE model.* Measurement errors may affect the mapping relating our observables and the model-consistent latent factors. To tackle this issue, we enrich our set of measurement equations with observable-specific white-noise measurement errors whose a-priori distributions are (mutually independent) Inverse Gammas with mean 0.25 and standard deviation 2. Our results turn out to be basically unaltered. In particular, the posterior mean of ψ is 0.19, with a $[0.07, 0.31]$ 90% credible set, i.e. figures in line with our benchmark estimates. As for ϕ_s, the posterior mean reads 0.91 (with $[0.53, 1.29]$ as 90% credible set), a figure just slightly lower than that proposed in our benchmark analysis. As for the remaining structural parameters, our estimates are basically unaffected, apart from the long-run systematic policy reaction to inflation, which increases to about 2, and the persistence of the output shock, which goes up to 0.5. When shutting down the financial channels (i.e. when setting $\psi = \phi_s = 0$) and re-estimating the model, we record a deterioration of the marginal likelihood of over 11 log-points. Figure 5 depicts the responses conditional on our DSGE model being estimated with measurement errors.

- *Upper triangular matrix* $\widetilde{\boldsymbol{B}}$. One might think of reducing the distance between Cholesky-VAR and true impulse responses to a monetary policy shock by employing an *upper* triangular $\widetilde{\boldsymbol{B}}$ matrix, which we term $\widetilde{\boldsymbol{B}}_{UP}$. Such identification scheme, the argument goes, would allow the policy shock to have an immediate impact on all the variables of the VAR. Of course, in so doing one would misspecify the policy rule. In fact, according to this identification scheme, the policy rate would not react to contemporaneous realizations of inflation and output. However, the argument goes, the benefit from "correctly" identifying the timing of the impact of the monetary policy shock could overcome the cost of misspecifying the policy rule. However, letting $\widetilde{\boldsymbol{B}}_{UP}$ replace $\widetilde{\boldsymbol{B}}$, one realizes that the last row of $\boldsymbol{\varphi}_t = \widetilde{\boldsymbol{B}}_{UP}^{-1}\boldsymbol{B}\boldsymbol{u}_t$ is full, i.e. the linear relationship $\varphi_t^R = \beta_{41}\eta_t^\pi + \beta_{42}\eta_t^x + \beta_{43}\eta_t^s + \beta_{44}\eta_t^R$ still holds. Figure 6 proposes the responses conditional on this exercise.

A3 Bayesian estimation

To perform our Bayesian estimation we employed DYNARE, a set of algorithms developed by Michel Juillard and collaborators. DYNARE is freely available at http://www.dynare.org/. The Dynare manual, written by Adjemian, Bastani, Juillard, Mihoubi, Perendia, Ratto, and Villemot (2010), documents the main features of DYNARE.

The simulation of the target distribution is basically based on two steps.

- First, we initialized the variance-covariance matrix of the proposal distribution and employed a standard random-walk Metropolis-Hastings for the first $t \leq t_0 = 20,000$ draws. To do so, we computed the posterior mode by the 'csminwel' algorithm developed by Chris Sims. The inverse of the Hessian of the target distribution evaluated at the posterior mode was used to define the variance-covariance matrix C_0 of the proposal distribution. The initial VCV matrix of the forecast errors in the Kalman filter was set to be equal to the unconditional variance of the state variables. We used the steady-state of the model to initialize the state vector in the Kalman filter.

- Second, we implemented the 'adaptive Metropolis' (AM) algorithm developed by Haario, Saksman, and Tamminen (2001) to simulate the target distribution. Haario, Saksman, and Tamminen (2001) show that their AM algorithm is more efficient that the standard Metropolis-Hastings algorithm. In a nutshell, such algorithm employs the history of the states (draws) to 'tune' the proposal distribution suitably. In particular, the previous draws are employed to regulate the VCV of the proposal density. We then exploited the history of the states sampled up to $t > t_0$ to continuously update the VCV matrix C_t of the proposal distribution. While not being a Markovian process, the AM algorithm is shown to possess the correct ergodic properties. For technicalities, refer to Haario, Saksman, and Tamminen (2001).

We simulated two chains of 400,000 draws each, and discarded the first 75% as burn-in. To scale the variance-covariance matrix of the chain, we used a factor so to achieve an acceptance rate belonging to the [23%,40%] range. The stationarity of the chains was assessed via the convergence checks proposed by Brooks and Gelman (1998). The region of acceptable parameter realizations was truncated so to obtain equilibrium uniqueness under rational expectations.

As typically done in the literature, we discarded all the draws not implying a unique equilibrium of the system. Notably, in presence of financial indicators in the IS curve, the standard Taylor principle does not apply anymore. For a discussion of the uniqueness conditions, see Nisticò (2007) and Airaudo, Nisticò, and Zanna (2008).

As for our prior densities, the key coefficients distinguishing our model from the baseline new-Keynesian DSGE framework (featuring no feedback from stock prices to the rest of the system) are ψ and ϕ_s. We assume fairly diffuse Normal distributions centered at zero for both these parameters. Hence, the data are free to decide the sign (as well as the magnitude) of the systematic macro-finance relationship. The economic interpretation of these relationship suggest that these parameters should take non-negative values. However, instead of imposing the economically sensible positive sign on these two parameters, we 'let the data speak' and impose symmetric priors centered at zero. Therefore, results in favor of positive values for such coefficients will be clearly data-driven.

As it is conventional for quarterly analysis, we fix the discount factor β to 0.99 (corresponding to an annual discount rate of approximately 4%) prior to estimation. Table 1 collects our prior densities, which are very standard. Given the vector $\boldsymbol{\xi} = [\beta, \alpha, \kappa, w_x, \psi, \delta_x, \lambda, \delta_s, \phi_\pi, \phi_x, \phi_s, \phi_R, \rho_\pi, \rho_x, \rho_R, \rho_s, \sigma_\pi, \sigma_x, \sigma_{R,}\sigma_s]'$ of structural parameters, the vector of endogenous variables $\boldsymbol{z}_t = [x_t, \pi_t, R_t, s_t]'$, the vector of shocks $\boldsymbol{\varepsilon}_t = [\varepsilon_t^x, \varepsilon_t^\pi, \varepsilon_t^s, \varepsilon_t^R]'$, the set of innovations $\boldsymbol{\eta}_t = [\eta_t^x, \eta_t^\pi, \eta_t^s, \eta_t^R]'$ and the vector of observable variables we aim at tracking $\boldsymbol{Y}_t = [x_t^{obs}, \pi_t^{obs}, R_t^{obs}, s_t^{obs}]'$, we write the model in state space form, we relate the latent processes to the observable variables via the measurement equations, and we employ the Kalman filter to evaluate the likelihood $L(\{\boldsymbol{Y}_t\}_{t=1}^T \mid \boldsymbol{\xi})$. The posterior distribution $p(\boldsymbol{\xi} \mid \{\boldsymbol{Y}_t\}_{t=1}^T)$ is then proportional to the product of the likelihood function $L(\{\boldsymbol{Y}_t\}_{t=1}^T \mid \boldsymbol{\xi})$ and the priors $\Pi(\boldsymbol{\xi})$.

A4 Further considerations on financial conditions indexes

A key choice for our analysis is the empirical counterpart for the 'financial soundness' indicator s_t. As discussed above, financial indicators tend to comove, but different indications on the 'financial momentum' may sometimes arise (Hakkio and Keeton (2009), DeGraeve (2008), Gilchrist, Yankov, and Zakrajsek (2009), and Castelnuovo and Nisticò (2010)). The KCFSI developed by Hakkio and Keeton (2009) collects information coming from eleven different financial stress indicators commonly considered by financial analysts and policymakers. The financial variables they consider belong to two main categories, i.e. yield spreads and asset price behavior, and were chosen to satisfy three criteria: i) they should have been available at monthly frequencies at least since 1990, ii) they should be market prices or yields, and iii) they should represent at least one of the five financial stress features identified by the Kansas City Federal Reserve (among others, increased uncertainty about assets' fundamental values, decreased willingness to hold risky assets, flights to quality or liquidity).[17] Hakkio and Keeton (2009) construct the KCFSI using a principal component procedure. Using this procedure, the coefficients of the financial variables are chosen so that the KCFSI explains the maximum possible amount of total variation in the variables. Hence, the loadings assigned to the different financial indicators are computed via the method of principal components so to maximize the total variation in the eleven variables explained by the KCFSI. Positive (negative) realizations of the indicator reflect a level of financial stress higher (lower) than its long term average. Hatzius, Hooper, Mishkin, Schoenholtz, and Watson (2010) document the predictive ability of the KCFSI versus alternative Financial Condition Indexes (FCIs). They find that, over the past decade, the KCFSI performed near the

[17] The list of indicators includes a variety of spreads such as the 3-month LIBOR/T-Bill spread (TED spread), the 2-year swap, the off-the-run/on-the-run 10-year Treasury spread, the Aaa/10-year spread, the Baa/Aaa spread, the high-yield bond/Baa spread, and the consumer ABS/5-year Treasury spread. The index is also composed by measures of risk or perceived stress such as the correlation between returns on stocks and Treasury bonds, the implied volatility of overall stock prices (VIX), the idiosyncratic volatility of bank stock prices, and the cross-section dispersion of bank stock returns. Hakkio and Keeton (2009) propose an in-depth discussion of these indicators.

average of the FCIs, and it can therefore be taken as the 'representative' composite indicator among the FCIs they focus on.[18]

The use of a composite indicator is connected to the idea of 'data-rich environment' advocated by Boivin and Giannoni (2006a) and Canova and Ferroni (2011). These papers employ large data-sets to reduce the distortions due to a 'limited-data' approach. The mapping between the set of available observables and the model-consistent latent factors is obtained via a set of measurement equations featuring observable-specific loadings and measurement errors. If the DSGE model correctly represents the DGP, consistent estimates of the weights assigned to the observables employed to estimate the dynamic framework are obtained. Unfortunately, despite the remarkable improvements in the construction of DSGE models occurred for the last years, these frameworks are still likely to be misspecified. Our choice is to employ the KCFSI, which is constructed with no explicit reference to any structural model, and it is therefore robust to model misspecification. Given that the KCFSI is built up to capture the evolution of the U.S. financial stress, we switch its sign to obtain a measure of 'financial soundness', i.e. an indicator whose positive (negative) realizations indicate a degree of financial soundness above (below) its long term average (recall that we normalize its mean to zero).[19]

Figure 7 plots two well known and widely used financial spreads, the BAA-AAA wedge and the AAA-Government Bond 10-year constant maturity rate spread over the 1990:II-2008:II sample. The BAA-AAA starts increasing before the 1991 recession and hits its local peak in the middle of the downturn. Differently, the AAA-10 year spread does not predict the 1991 recession, starts increasing during the crises, and hits its local maximum way later. However, as for the 2001 recession and the economic collapse begun in 2007, the AAA-10 year spread increases well in advance with respect to the crisis (above all, the 2001 one), and features peaks in the midst of such crisis. In contrast, the BAA-AAA spread turns out to be a 'lagging indicator' of the 2001 recession, and features very mild anticipatory properties of the current financial crisis. Somewhat not surprisingly, the sample correlation between these two indexes, while being positive, is

[18] The different FCIs they consider are produced by Bloomberg, Citi, Deutsche Bank, Goldman Sachs, the Federal Reserve of Kansas City, Macroeconomic Advisers, and OECD.

[19] Note that the KCFSI is a standardized measure of financial stress (it features zero mean and unitary variance). Consequently, the estimated coefficients have to be interpreted with care. However, our interest is that of establishing i) if financial soundness is a relevant ingredient to describe the U.S. macroeconomic dynamics; ii) if the Federal Reserve has systematically reacted to movements in the financial stress; and, most importantly, iii) to what extent macroeconomic shocks have triggered interactions at a macro-finance level, with a particular attention for the effects of a monetary policy shock. Then, our analysis can be meaningfully carried out with this standardized measure of financial conditions.

far from spectacular, i.e. 0.34.

Is the KCFSI superior in terms of predictive ability as for the evolution of the business cycle? Figure 7 contrasts the KCFSI with the BAA-AAA and the AAA-Government Bond 10-year constant maturity rate spreads. The KCFSI picks up both past episodes of financial stress such as the 1990-1991 and 1998-2002 recessions, and the credit crisis began in the summer of 2007. Hakkio and Keeton (2009) show that the KCFSI significantly correlates with a variety of measures of tightening of credit standards as well as some popular business cycle indicators. Further discussions are provided in Hakkio and Keeton (2009).

Finally, we conduct an 'external validation' exercise to assess the reliability of our DSGE model-consistent measure of financial shocks. Hatzius, Hooper, Mishkin, Schoenholtz, and Watson (2010) estimate a new Financial Condition Index (FCI) by extracting the signal embedded by forty-five subindexes including price, quantity, survey, liquidity, and credit subindexes. The extraction of the signal is performed by appealing to principle component techniques. Importantly, the measure they propose is purged to get rid of the information already embedded by standard macroeconomic indicators such as past real GDP growth, inflation, and the federal funds rate. Therefore, their purged FCI is a proxy of U.S. financial shocks. We then contrast the estimates of the U.S. financial shocks proposed by Hatzius, Hooper, Mishkin, Schoenholtz, and Watson (2010) with our estimated series of model consistent shocks $\boldsymbol{\eta}^s$.[20] Figure 8 depicts these two measures. Firstly, there is comovement between these two measures, with a degree of sample correlation equal to 48%. Secondly, the two indicators share the same sign 63% of the times. Thirdly, both indicators clearly capture the financial crisis began in 2007 with a quick, dramatic drop with respect to their historical mean. All in all, we believe this external validation exercise to be reassuring on the ability of our model to identify the role of the U.S. financial shocks in the 1990-2008 period.

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[20] We consider the quarterly measure 'FCI with GDP, Inflation and Fed Funds Purged' in the 'fci_data_1_watson' spreadsheet available at Mark Watson's webpage, i.e. http://www.princeton.edu/~mwatson/wp.html .

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Param.	*Prior Dens.*	*Posterior Means* [5h,95th]	
		Model with fin. cond's	Standard NK model
α	$\beta(0.5, 0.28)$	0.04 [0.00,0.10]	0.04 [0.00,0.10]
κ	$\Gamma(0.05, 0.01)$	0.03 [0.02,0.04]	0.03 [0.02,0.04]
w_x	$\beta(0.5, 0.28)$	0.39 [0.27,0.50]	0.50 [0.39,0.62]
ψ	$N(0, 0.5)$	0.17 [0.07,0.27]	–
δ_x	$\Gamma(0.1, 0.05)$	0.09 [0.02,0.15]	0.08 [0.03,0.13]
λ	$\Gamma(0.05, 0.025)$	0.02 [0.01,0.04]	0.02 [0.00,0.03]
δ_s	$\Gamma(0.1, 0.05)$	0.12 [0.05,0.19]	0.03 [0.01,0.06]
ϕ_π	$N(2.0, 0.3)$	1.62 [1.16,2.09]	1.72 [1.21,2.20]
ϕ_x	$\Gamma(0.25, 0.1)$	0.55 [0.38,0.71]	0.52 [0.33,0.71]
ϕ_s	$N(0, 0.5)$	1.15 [0.74,1.56]	–
ϕ_R	$\beta(0.5, 0.28)$	0.89 [0.86,92]	0.89 [0.86,0.92]
ρ_π	$\beta(0.5, 0.28)$	0.61 [0.48,0.74]	0.61 [0.48,0.75]
ρ_x	$\beta(0.5, 0.28)$	0.15 [0.00,0.30]	0.36 [0.08,0.64]
ρ_s	$\beta(0.5, 0.28)$	0.84 [0.77,0.90]	0.79 [0.74,0.84]
ρ_R	$\beta(0.5, 0.28)$	0.42 [0.22,0.62]	0.55 [0.41,0.71]
σ_π	$I\Gamma(0.25, 2)$	0.10 [0.07,0.14]	0.10 [0.07,0.13]
σ_x	$I\Gamma(0.25, 2)$	0.29 [0.21,0.37]	0.22 [0.12,0.30]
σ_s	$I\Gamma(0.25, 2)$	0.08 [0.07,0.09]	0.09 [0.08,0.11]
σ_R	$I\Gamma(0.25, 2)$	0.07 [0.05,0.09]	0.06 [0.05,0.08]
$Log(ML)$		-15.02	-28.96

Table 1: **Bayesian estimates of alternative models.** Full sample and subsample posterior densities. Prior densities: Figures indicate the (mean,st.dev.) of each prior distribution. Posterior densities: Figures indicate the posterior mean and the [5th,95th] percentile of the estimated densities. Details on the estimation procedure provided in the text and Appendix. Marginal likelihoods computed via Laplace Approximation.

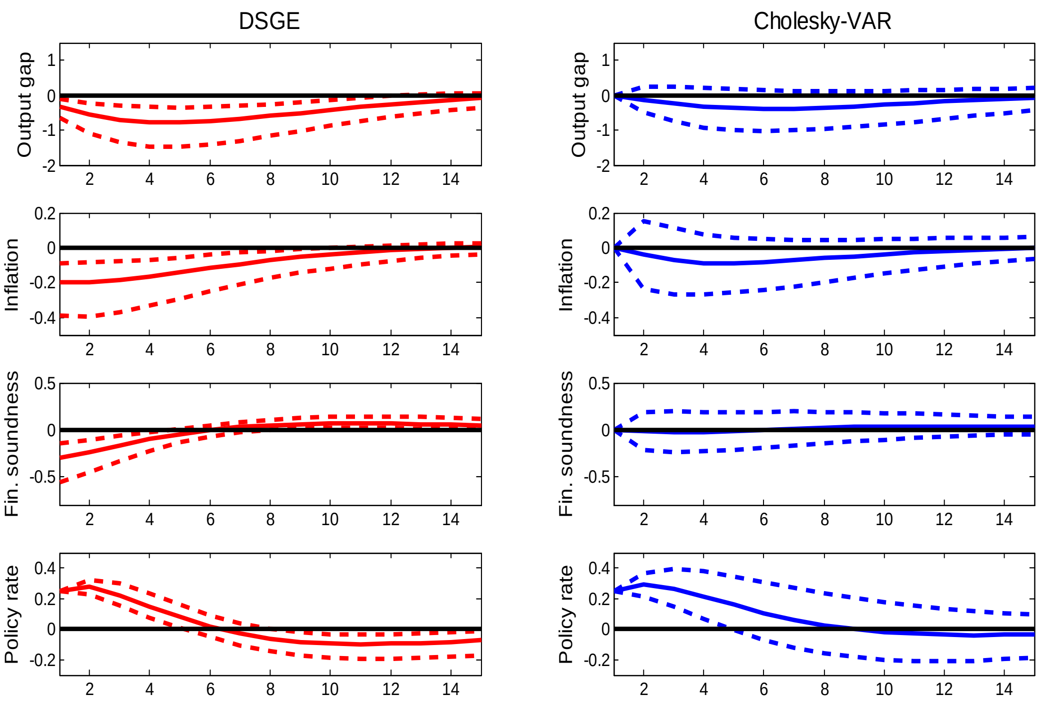

Figure 1: **Impulse Responses to a Monetary Policy Shock: DSGE vs. Cholesky-VAR estimated with simulated data.** Red lines: mean and [5th,95th] percentiles of the distribution of the impulse responses conditional on our estimated DSGE model. Blue lines: mean and [5th,95th] percentiles of the impulse responses conditional on estimated Cholesky-VARs. VAR(2) estimated with pseudo data (DGP: estimated DSGE model).

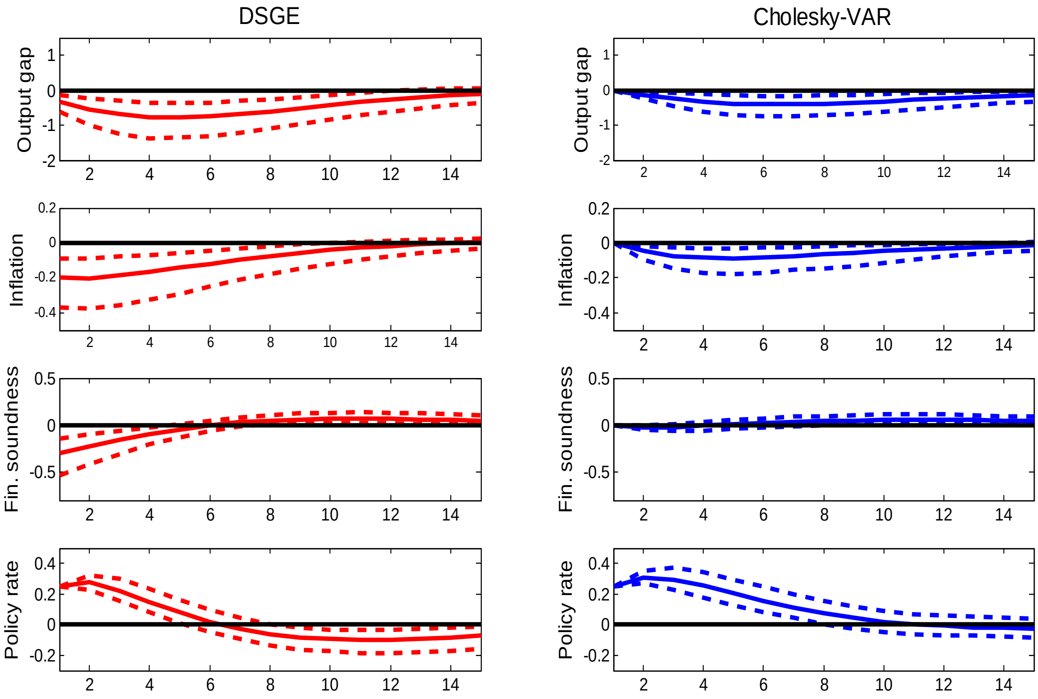

Figure 2: **Impulse Responses to a Monetary Policy Shock: DSGE vs. Cholesky-VAR estimated with simulated data: DSGE-model consistent A(L) matrices.** Red lines: mean and [5th,95th] percentiles of the distributions conditional on the estimated DSGE model. Blue lines: mean and [5th,95th] percentiles of the distributions conditional on estimated Cholesky-VARs. VAR(2) estimated with pseudo data (DGP: estimated DSGE model).

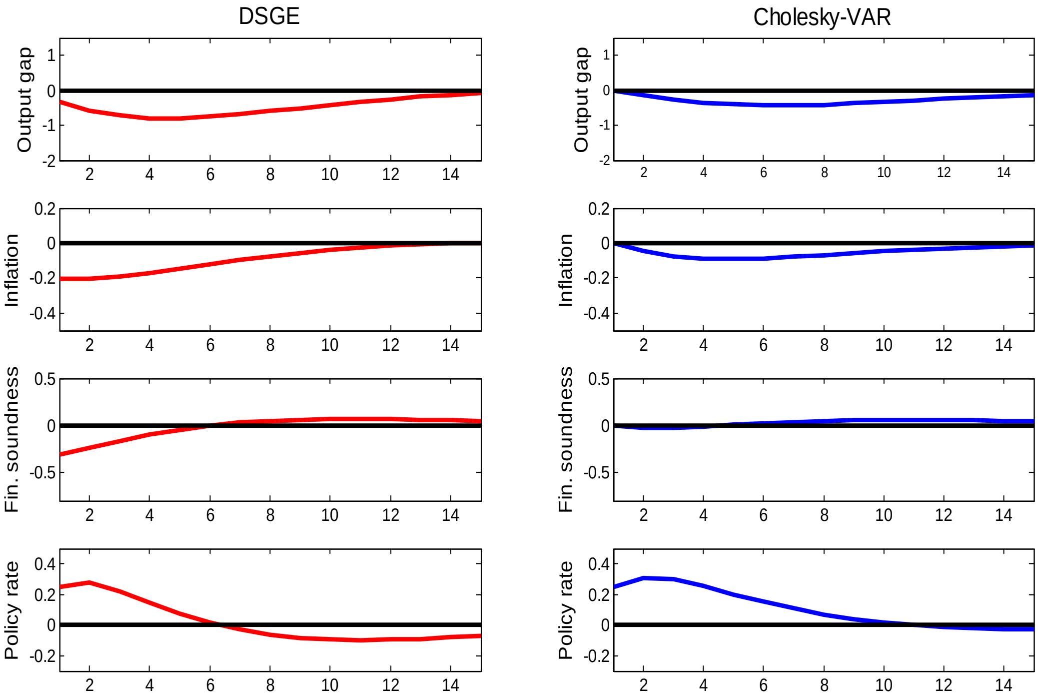

Figure 3: **Impulse Responses to a Monetary Policy Shock: DSGE vs. Cholesky-VAR estimated with simulated data: Population moments.** Red lines: mean and [5th,95th] percentiles of the distributions conditional on the estimated DSGE model. Blue lines: mean and [5th,95th] percentiles of the distributions conditional on estimated Cholesky-VARs. VAR(2) estimated with pseudo data (DGP: estimated DSGE model).

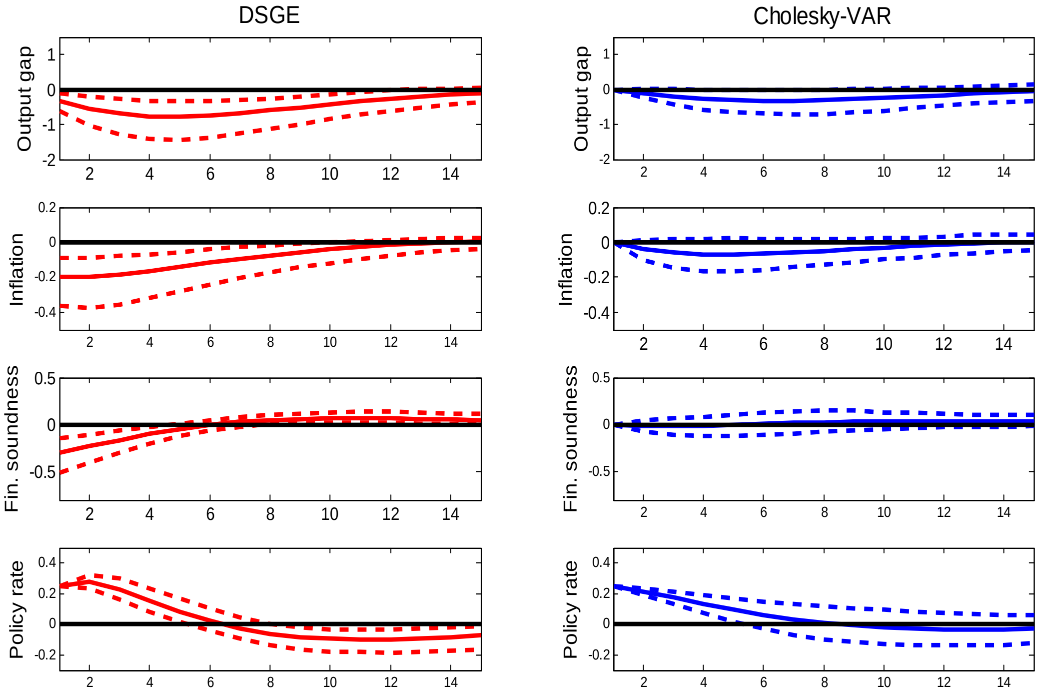

Figure 4: **Impulse Responses to a Monetary Policy Shock: DSGE vs. Cholesky-VAR estimated with simulated data: Optimal lag selection.** Red lines: mean and [5th,95th] percentiles of the distributions conditional on the estimated DSGE model. Blue lines: mean and [5th,95th] percentiles of the distributions conditional on estimated Cholesky-VARs. VAR(p) estimated with pseudo data (DGP: estimated DSGE model). Number of lags p selected according to the Schwarz information criterion.

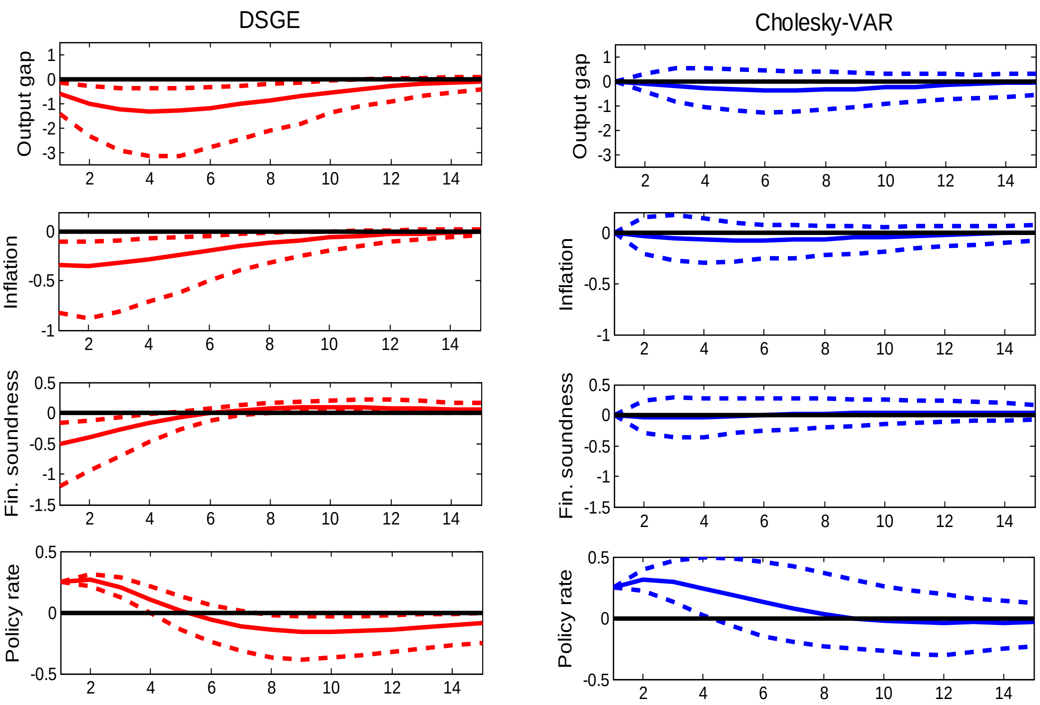

Figure 5: **Impulse Responses to a Monetary Policy Shock: DSGE vs. Cholesky-VAR estimated with simulated data: Measurement errors.** Red lines: mean and [5th,95th] percentiles of the distributions conditional on the estimated DSGE model. Blue lines: mean and [5th,95th] percentiles of the distributions conditional on estimated Cholesky-VARs. VAR(p) estimated with pseudo data (DGP: estimated DSGE model). Number of lags p selected according to the Schwarz information criterion. Measurement errors.

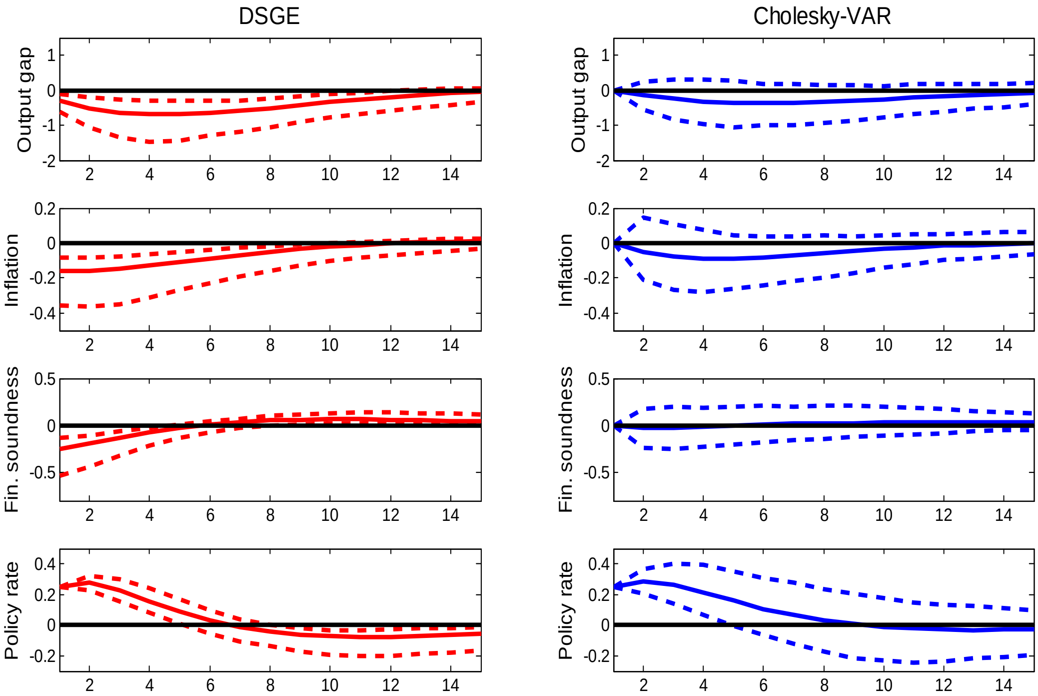

Figure 6: **Impulse Responses to a Monetary Policy Shock: DSGE vs. Cholesky-VAR estimated with simulated data: Upper triangular matrix for the contemporaneous relationships.** Red lines: mean and [5th,95th] percentiles of the distributions conditional on the estimated DSGE model. Blue lines: mean and [5th,95th] percentiles of the distributions conditional on estimated Cholesky-VARs. VAR(2) estimated with pseudo data (DGP: estimated DSGE model).

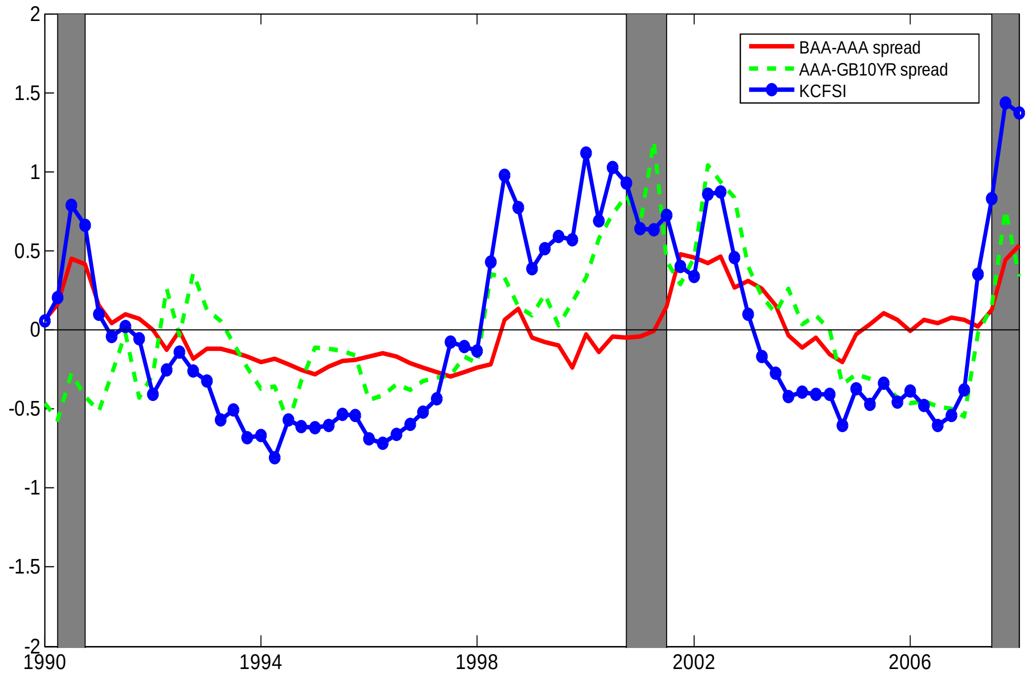

Figure 7: **Financial Stress Indicators: Comparison.** Sample: 1990:II-2008:II, demeaned data. Observables feature zero mean. The horizontal axis reports second quarters, i.e. 1990:II, 1994:II, and so on.

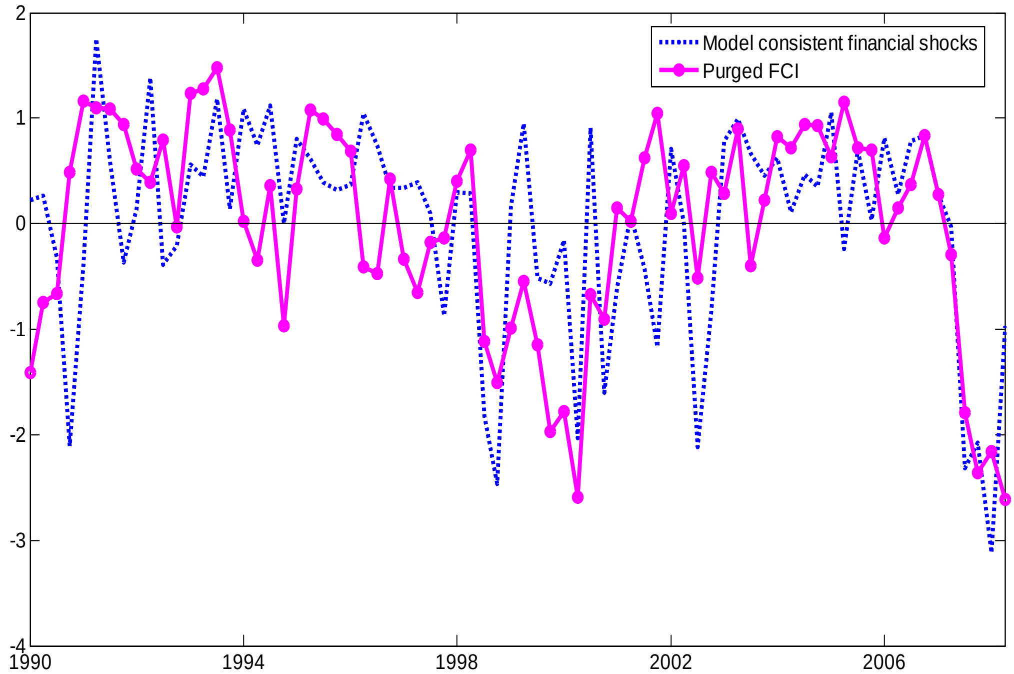

Figure 8: **Measures of Financial Shocks: Comparison.** Blue dotted line: DSGE model-consistent financial shocks (smoothed values). Magenta circled line: Financial shocks as estimated by Hatzius et al (2010).