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Abstract

We identify a 'risk news' shock in a vector autoregression (VAR), modifying Barsky and Sims's procedure, while incorporating sign restrictions to simultaneously identify monetary policy, technology and demand shocks. The VAR-identifed risk news shock is estimated to account for around 2%–12% of business cycle fluctuations depending on which risk proxy we use; regardless, contemporaneous risk and risk news shocks together account for about 20%. This is substantially lower than the 60% reported in Christiano, Motto, and Rostagno's full-information exercise. We fit a DSGE model with financial frictions to these impulse responses and find that, in order to match the fall in consumption recorded by the VAR, we have to allow for 75% of consumers to be living hand-to-mouth.

Key words: News shock, business cycles, risk, financial frictions, vector autoregression.

JEL classification: C10, C32, E20, E30, E58, G21.

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Summary

How does uncertainty affect the financial system and the aggregate behaviour of the economy? Recent events have led to increasing attention to the question of how uncertainty might shape the depth and duration of financial and economic crises. In addition, macroeconomists have emphasised the role of shocks originated in the financial system in driving macroeconomic fluctuations. This paper develops a multivariate statistical model as well as a theoretical framework to show that uncertainty related to financial markets has played a considerable role in explaining the past 30 years of US business cycles.

In our model, a financial disturbance is defined as an exogenous process that drives the dispersion of returns on investment. As these forces govern the state of investment risk in the economy, we refer to these perturbations as 'risk shocks'. Moreover, we distinguish between contemporaneous (unanticipated) and news-type (anticipated) components of these exogenous processes. By doing so, we build on recent academic papers which suggest that most of the economic effects of financial shocks occur as economic agents respond to advance information, 'news', about the future realisation of these processes. Some of these papers find that the overall effects of these disturbances to financial markets account for about 60% of output fluctuations in the United States.

The empirical part of our paper develops a multivariate statistical model which we use to identify risk and risk news shocks in the data. This allows us to quantify and distinguish the partial impact of risk and risk news shock from that of other, more standard, macroeconomic shocks such as monetary policy, supply and demand shocks.

Our empirical results suggest that the combined effects of risk and risk news shocks explain approximately 20% of US output fluctuations over the 1980-2010 period. This is a more modest effect than that found in previous studies. Nevertheless, we find that these types of financial disturbances have a large impact on the federal funds rate, suggesting that revelations about future uncertainty induce a vigorous and protracted response of the US monetary policy authority. With central bank rates pinned at their zero lower bound for some time now in the United States, United Kingdom and Japan, our results would suggest that risk news shocks may have impacted on the real economy more recently, and could in the future, until such time as conditions allow the central bank to raise rates to more normal levels.

The theoretical part of this study then develops a relatively standard quantitative "dynamic stochastic general equilibrium" (DSGE) model. Models of this type capture the evolving and interconnected dynamics of the entire economy, allowing for the presence of random ("stochastic") shocks. The model is made realistic by the presence of various nominal and real frictions. These include the assumption that a fraction of households are 'non-Ricardian', meaning that they do not base their decisions on their expectations about future income, as they do not have access to financial markets and their consumption is a function of their current (rather than future) disposable income. In addition, our model features a form of 'financial accelerator' mechanism stemming from the riskiness of business loans in the model, as the returns on projects are subject to idiosyncratic (ie, firm specific) shocks. We refer to the

distribution of these idiosyncratic shocks as risk shocks, reflecting on the underlying investment risk in our model economy. A sufficiently adverse draw from this distribution can make a particular borrowing firm insolvent, which causes lenders to charge an *ex ante* higher interest rate compared to the risk-free rate. This premium moves countercyclically with business equity (borrower's net worth) and procyclically with investment risk.

The estimated version of our theoretical model reveals that in order to match the quantitative responses of risk shocks implied by our statistical analysis, the degree of real rigidities in the model such as the fraction of non-Ricardian households must be remarkably high. From this, we conclude that there is still more work to be done in order to improve the endogenous propagation of financial shocks in DSGE models.

1 Introduction

Interest in the causes of business cycles has increased since what appears to be the end of the so-called 'Great Moderation', which has been followed by an unusually severe and long-lasting contraction. The severity of this recent contraction, and its proximate origin in the financial sector, has sparked research activity seeking to isolate and quantify the contribution of what some term 'financial shocks'. This paper seeks to further this effort. The focus on financial shocks derives in part from the recognition that business cycle models with financial frictions only weakly propagate other, conventional shocks like technology shocks. This can be verified by comparing the with and without frictions versions of Bernanke and Gertler (1989) and Kiyotaki and Moore (1997), and the same thing is true of sticky price versions of related models built subsequently (for example, Bernanke, Gertler, and Gilchrist (1999) (BGG), Iacoviello (2005)). As such, these models cannot assign prominent roles to financial factors in causing or aggravating business cycles, something that jars with informal accounts - such as those deployed by central bankers and other policymakers - of the last several years. However, financial shocks - disturbances that hit elements of the model that define the financial frictions - can be shown to generate large fluctuations in their own right. This point is elegantly made by Hall (2011) who studies exogenous disturbances to the wedges between the return to saving, and the users of funds in the business and household sector. Christiano, Motto, and Rostagno (2013) (CMR) modified a medium-scale DSGE model with sticky prices and wages, and other frictions, to include financial frictions in the style of BGG, with a view to studying the contributions of random fluctuations in risk to the US business cycle. In their model, entrepreneurs who build capital goods (which are sold on to the sticky-price intermediate firms recognizable from the standard DSGE model) are hit by an idiosyncratic shock, which leads to cross-sectional variation in the amount of effective capital that is made from a given quantity of capital inputs. They finance themselves by borrowing from banks. When the cross-sectional variance of capital-goods builders' risk increases, this increases the chance of default, and banks demand a higher spread to compensate. In addition to allowing for fluctuations in risk of this sort, CMR allow that these fluctuations could be pre-announced, or, in the jargon of the business cycle literature, that there could be risk news shocks. CMR estimate their model using Bayesian maximum likelihood methods, backing out the shock from 10 US time series, and compute that time-variation in risk and risk news accounts for 60% of the volatility in US output growth in the post-1980 period.

This is a very striking result. The predominance of the risk (and risk news) shocks pushes to the background other shocks that were highlighted previous, similar work: for example, technology shocks as in Kydland and Prescott (1982) (KP); shocks to the discount rate as in Smets and Wouters (2007) (SW); shocks to the marginal efficiency of investment Justiniano, Primiceri, and Tambalotti (2010) (JPT); and mark-up shocks. It is natural with a new result like this to look for ways to scrutinize and evaluate it, and this is what our paper does. The strategy we take is to use VAR methods to find a more agnostic way to isolate risk and risk news shocks, and quantify their contribution. Does CMR's result, derived from taking a very particular stand on the data generating process, hold up when we use methods that are appropriate if the CMR model were the data generating process, but are also going to work in a wider class of similar models? This general strategy we have adopted has echoes in past work. For example, the earliest real business cycle papers which claimed that technology shocks alone could account for US business cycles (e.g. KP) were followed by papers that scrutinized this claim by trying to identify technology shocks in VARs, Gali (1999) being a case in point, famously sceptical of the RBC claim based on observing that technology shocks induce a change in hours that from the point of view of the model was counterfactual.

To identify risk and associated news shocks in a VAR, we use a modification of the method of Barsky and Sims (2011) (BS, hereafter) which they applied to the task of recovering technology and corresponding news shocks. In their work, technology, measured as modified Solow residuals (following Basu, Fernald, and Kimball (2006)), was treated as an observable. News about technology was something orthogonal to technology today, but which contributes maximally to the forecast error variance of technology up to some finite horizon in the future. Analogously, we treat risk as an observable, (using as proxies either the VIX, or the dispersion across stock returns computed from the CRSP database). A risk news shock is taken to be a shock that is orthogonal to the risk proxy today, but contributes maximally to fluctuations in it up to some finite future horizon. The modification beyond BS's method is that we can allow for the risk news shock to be restricted to induce comovements between our VARs variables of particular signs. For example, consistent with CMR's DSGE model, we impose that a forewarning of a future increase in risk lowers the growth in GDP, investment and net worth, and this despite prompting the central bank to cut the policy rate. We can also use the addition of sign restrictions to identify other more familiar shocks (monetary policy and technology shocks, for example) so that we can arrive at a more complete picture of the relative contribution of different shocks to the business cycle.

Our findings reveal that risk and risk news shocks were important drivers of the business cycle, but not dominant. We estimate that in the US risk news shocks contributed somewhere between 2% and 12% of the total volatility in output (depending on which of two risk proxies we use). The contemporaneous and news shocks to risk together contribute about 20% (regardless of which risk proxy we use). This combined contribution contrasts with a value of 60% in CMR, that comes from using full information techniques to estimate a DSGE model with financial frictions with risk and risk news shocks. These values are associated with the median VAR in a Bayesian posterior. The $2.5th$ and $97.5th$ percentile values correspond to numbers of 11% and 74% respectively, so the very stark contrast between central estimates in our paper and CMR should not be taken too literally.

Although risk news shocks on their own contribute modestly to fluctuations in output, they matter a lot for the central bank policy rate, which, as we have said, fights to counter the effect of the risk news shock, suggesting that were it not for the actions of the central bank these shocks could be more damaging. With central bank rates pinned at their zero lower bound for some time now in the US, UK and Japan, our results would suggest that risk news shocks may have impacted on the real economy more recently, and could in the future, until such time as conditions allow the central bank to raise rates to more normal levels, (that is, supposing that unconventional monetary policies are also constrained or are at best imperfect substitutes for interest rate policy).

In a final exercise in the paper, we take the DSGE model developed by Christiano, Eichenbaum, and Evans (2005) and SW, modified to incorporate BGG financial frictions, and we put it to work in two ways. First, we use data generated from this model to ask whether an econometrician following our method could correctly identify the risk news shock and compute the associated impulse responses (echoing the Monte Carlo test that BS deployed in a simple RBC laboratory to test whether news shocks to technology could be isolated accurately). We find that the method does very well. Second, we estimate the model using minimum distance methods and inspect how closely the model can match the impulse responses to the risk news shock identified by the VAR, and what the minimum distance estimate has to say about the kind of DSGE model needed to match those impulse responses. We find that the model can get reasonably close to these responses if we modify it to incorporate the possibility that some consumers are not dynamic optimizers but instead are rule-of-thumb (ROT) consumers (following Gali, Lopez-Salido, and Valles (2007) and Cogan, Cwik, Taylor, and Wieland (2010)). In the absence of ROT consumers the model generates an *increase* in consumption following the risk news shock due to the vigorous and protracted cut in central bank rates in responses to risk news shock, which is counter-factual, (at least insofar as the VAR impulse responses can be taken as a 'fact'). The modification to include ROT consumers takes the model some way from the benchmark: our minimum distance estimation suggests that we need 75% of consumers to live hand-to-mouth to produce the best fit. The model with ROT consumers displays far more volatility in inflation and GDP growth in response to the risk news shock than its counterpart with fully rational consumers. This said, the minimum distance estimates produce a model that only weakly propagates risk news shocks relative to the VAR, and for this reason requires a standard deviation of risk news shocks about 4 times that estimated in the VAR. This weak propagation is related to the estimated weakness of the financial frictions in the model, in turn related to the low cost of bankruptcy on auditing, a key parameter in the original BGG model, and in our SW+BGG model. If we turn up the degree of financial acceleration, so to speak, by using higher values for this cost of auditing, e.g. the values in the BGG or CMR papers, then the number of ROT consumers falls somewhat, to 50%, but still leaves us with a model that is drastically modified relative to the model populated entirely by optimizing consumers.

2 Related Literature

The closest antecedents to our work have already been mentioned: CMR, whose paper gives rise to our quest to look for a more agnostic way of identifying their risk and risk news shocks, and BS, whose news shock identification method we modify to incorporate sign restrictions. Before going on, we try to locate what we have done in the context of other strands of research that predated our work.

The first strand we mention is work studying financial shocks within business cycle models, which, to recap derive their interest from being able to generate large fluctuations in their own right and circumvent the model's weak propagation of conventional shocks. Justiniano, Primiceri, and Tambalotti (2011) estimate a DSGE model with a Hall-like shock to the transformation of savings into capital: since this is the job of financial intermediation, one can interpret such a shock as measuring financial frictions, or the efficiency of financial intermediation. Other papers take objects that were parameters in financial friction models, and allow them to be time-varying (in the same vein as CMR). Fuentes-Albero (2012) considers a shock to the cost of bankruptcy in BGG; Nolan and Thoenissen (2009) and Christiano, Motto, and Rostagno (2008) consider shocks to the entrepreneurs' net worth accumulation equation in BGG; Gertler and Karadi (2011) consider shocks to the net worth of private banks, who face BGG-like financial frictions in raising funds; Iacoviello (2013) examines shocks to the repayments of households who were lent to by financially constrained banks. Finally, Jermann and Quadrini (2012) study a model with shocks to the costs of changing the firm's debt/equity mix. CMR's risk (and corresponding news) shock, which we are seeking to uncover in the VAR, is self-evidently different.

A recent VAR literature on financial shocks also bears on what we have done. Fornari and Stracca

(2012) identify a financial shock as a shock that causes the relative share price of the financial sector to change, (with some other restrictions). A few papers identify financial shocks by estimating a dynamic factor model, and then recovering structural shocks to the factors by imposing restrictions on the movement of certain financial series amongst a large panel of observables. Work in this mould includes, amongst others: Dahlhaus (2012), Boivin, Giannoni, and Stevanovic (2013) and Helbling, Huidrom, Kose, and Otrok (2011). Gilchrist, Yankov, and Zakrajsek (2009) differs from papers that seek to orthogonalize credit shocks using spread series like those mentioned here by first extracting the component of individual bond spreads that is unrelated to causes unrelated to credit supply (e.g. own share price and macroeconomic conditions in general). Our work differs from these papers in that it follows the lead of the modified BGG model in looking for the ultimate source of financial shocks in changes in cross-sectional risk. This entails some costs, since we lose the agnosticism embedded in these more generalized financial shock papers, but we gain interpretability by attempting to measure cross-sectional risk and identifying the risk shock accordingly.

The closest empirical exercise to ours is contained in Sim, Zakrajsek, and Gilchrist (2010). They identify contemporaneous risk shocks in a VAR using i) data on the cross section of individual firm returns from the same CRSP data we exploit (filtered in ways that we do not employ) and ii) a recursive ordering that is consistent with how we recover our contemporaneous risk shocks. Our main point of departure is to identify also risk news shocks, and use the impulse responses to these shocks to see what they imply about the nature of the SW+BGG model. The point of their work is to explain that the risk shocks themselves have no effect except via financial frictions. This is true also of the SW+BGG model we subsequently estimate, and of the CMR model. Our focus is different, namely, to scrutinize the full information results on the contribution of risk and risk news shocks to business cycles.

Another strand of work that clearly relates to what we have done is the general business cycle work on news shocks. Once one adopts rational expectations as a working assumption, it is natural to conjecture that agents may react to advance warnings of future events, of which there are many compelling examples (e.g. policy changes that are announced in advance). As Jaimovich and Rebelo (2009) point out, early versions of this insight go back to Beveridge (1909), Pigou (1927) and Clark (1934). Barro and King (1984) and Cochrane (1994) were aware that news shocks were not good candidates for explaining business cycles, since positive TFP news caused hours to fall and consumption to rise, which was contrary to the unconditional correlation in the data. However, Jaimovich and Rebelo (2009) showed that news shocks could generate a positive comovement in the RBC model if the wealth effect on labour supply was neutralized (together with other modifications). One way of isolating these news shocks is to encode them within an explicit business cycle model and use full information methods. Schmitt-Grohe and Uribe (2012) follow this approach, modelling news at two time horizons for seven different shocks in a DSGE/RBC model. They found that news shocks in total accounted for about half of fluctuations in US output. CMR's paper adopts the same full information estimation approach, but studies revelations about future changes in the cross section of returns to the entrepreneurs who borrow within a DSGE model with financial frictions.

A VAR literature on news shocks has grown up alongside this work on explicit business cycles models. In a collection of papers (Beaudry and Portier (2006), Dupaigne, Portier, and Beaudry (2007) and Beaudry and Lucke (2010)) Beaudry and co-authors identify news shocks to TFP in a VAR. Two schemes are used. In one, a news shock is a shock that is uncorrelated with today's TFP but causes a change in the stock price. In a second, a news shock is uncorrelated with today's TFP but causes a long-run change in TFP.

BS's strategy, which we modify, itself derives from Francis, Owyang, Roush, and DiCecio (2010) which identifies a technology shock as the object that contributes maximally to fluctuations in labour productivity at a long but finite horizon. Their 'max share' method, as they call it, was a way to employ the logic of looking for long-run restrictions, but without falling foul of the problems of imposing restrictions that hold at horizon infinity in a finite sample, previously noted by Sims (1972), Faust (1998) and Faust and Leeper (1997).

We conclude our quick tour of the literature by noting that the focus of this paper (as in CMR) is on fluctuations in the variance of the distribution of *idiosyncratic* disturbances to productivity. This is to be distinguished from the interesting and complementary work on time-series fluctuations in *aggregate* volatility.[1] Such work includes: Bansal and Yaron (2004) (impact of changes in aggregate consumption risk on asset prices), Bloom (2009), Justiniano and Primiceri (2008) (aggregate uncertainty in productivity and macro outcomes), Fernandez-Villaverde, Guerron-Quintana, Kuester, and Rubio-Ramirez (2011) and Born and Pfeifer (2011) (aggregate fiscal uncertainty), Mumtaz and Theodoridis (2012) (aggregate technology uncertainty in the open economy) and many others. The linearized DSGE model that we scrutinize with the VAR, (like all linear business cycle models), has no role for fluctuations in aggregate volatility, in this respect obeying certainty equivalence, and we leave to future research the question of disentangling movements in idiosyncratic and aggregate risk, and news about these objects.

3 Our Strategy for Identifying the Risk News Shock

As explained earlier, to complement the full information strategy in CMR we are going to identify the risk news shock in a VAR. We first estimate the VARs reduced-form parameters shrinking the posteriors using Bayesian, Minnesota-style priors. We then identify our risk news shock (and monetary policy, technology and demand shocks) using a combination of sign restrictions and a maximization step following BS (and their antecedents).

3.1 The Empirical Model

The first task is to lay out and estimate the reduced-form VAR, which we do using Bayesian, Minnesota-type priors. The shrinkage is necessary given that we have a ten variable VAR with 3 lags (the VAR order is consistent with the choice made by Smets and Wouters (2007)), which implies many parameters to be estimated relative to the degrees of freedom afforded by our 30 years of quarterly data.

To explain our method, we can take the general case of a vector autoregressive model of order K – VAR(K)

$$y_t = \sum_{i=1}^{K} \Theta_i y_{t-i} + u_t, \tag{3.1}$$

[1]Such fluctuations might also reasonably be described as 'risk shocks' but when we use this term we mean to refer only to changes in the distribution of idiosyncratic productivity.

where u_t is the $N \times 1$ vector of reduced-form errors that are normally distributed with zero and Σ variance-covariance matrix. The regression-equation representation of the latter system is

$$Y = X\Psi + V,$$

where $Y = [y_{h+1}, .., y_T]$ is a $N \times T$ matrix containing all the data points in y_t, $X = Y_{-h}$ is a $(NK) \times T$ matrix containing the h-th lag of Y , $\Theta = \begin{bmatrix} \Theta_1 & \cdots & \Theta_K \end{bmatrix}$ is a $N\times$ (NK) matrix, and $U = [u_{h+1}, .., u_T]$ is a $N \times T$ matrix of disturbances.

We deploy Minnesota-type priors (Doan, Litterman, and Sims, 1984; Litterman, 1986), and posterior inference is obtained as follows. It is assumed that the prior distribution of the VAR parameter vector has a Normal-Wishart conjugate form

$$\theta|\Sigma \sim N(\theta_0, \Sigma \otimes \Omega_0),\ \ \Sigma \sim IW(v_0, S_0), \tag{3.2}$$

where θ is obtained by stacking the columns of Θ. The prior moments of θ are given by

$$E[(\Theta_k)\, i, j] = \begin{cases} \delta_i & i = j, k = 1 \\ 0 & \text{otherwise} \end{cases},\ \ Var[(\Theta_k)\, i, j] = \lambda\sigma_i^2/\sigma_j^2,$$

and, as explained by Banbura, Giannone, and Reichlin (2010), they can be constructed using the following dummy observations

$$Y_D = \begin{pmatrix} \frac{diag(\delta_1\sigma_1...\delta_N\sigma_N)}{\lambda} \\ 0_{N\times(K-1)N} \\ .... \\ diag\,(\sigma_1...\sigma_N) \\ .... \\ 0_{1\times N} \end{pmatrix} \text{ and } X_D = \begin{pmatrix} \frac{J_K\otimes diag(\sigma_1...\sigma_N)}{\lambda} \\ 0_{N\times NK} \\ .... \\ 0_{1\times NK} \end{pmatrix}, \tag{3.3}$$

where $J_K = diag\,(1, 2, ..., K)$ and $diag$ denotes the diagonal matrix. The prior moments of (3.2) are just functions of Y_D and X_D, $\Theta_0 = Y_D X_D' \,(X_D X_D')^{-1}$, $\Omega_0 = (X_D X_D')^{-1}$, $S_0 = (Y_D - \Theta_0 X_D)\,(Y_D - \Theta_0 X_D)'$ and $v_0 = T_D - NK$. Finally, the hyper-parameter λ controls the tightness of the prior.

As is well known, and explained, for example, in (Kadiyala and Karlsson, 1997), the choice of a Normal for the prior distribution of VAR parameters conditional on variances, and the inverse-Wishart for variances, is convenient as these distributions are conjugate, leading to an expression for the posterior that can be evaluated analytically, rather than one that has to be approximated through MCMC sampling. Since our procedure entails computational intensity in other aspects (in particular there is going to be a maximization step, associated with identification, for each point in our posterior), this simplicity yields considerable practical benefits. Thus, formally, we have that:

$$\theta|\Sigma, Y \sim N(\bar{\theta}, \Sigma \otimes \bar{\Omega}),\ \ \Sigma|Y \sim IW(\bar{v}, \bar{S}), \tag{3.4}$$

where the bar denotes that the parameters are those of the posterior distribution. Defining $\hat{\Theta}$ and $\hat{U}$ as the OLS estimates, we have that $\bar{\Theta} = (\Omega_0^{-1}\Psi_0 + YX')(\Omega_0^{-1} + X'X)^{-1}$, $\bar{\Omega} = (\Omega_0^{-1} + X'X)^{-1}$, $\bar{v} = v_0 + T$, and $\bar{S} = \hat{\Theta}XX'\hat{\Theta}' + \Theta_0\Omega_0^{-1}\Theta_0 + S_0 + \hat{U}\hat{U}' - \bar{\Theta}\bar{\Omega}^{-1}\bar{\Theta}'$.

δ_i and σ_i denote the mean and variance of the priors for the diagonal, autoregressive coefficients in the VAR. These prior moments come from OLS estimates of AR(1) models estimated in each of the 10 variables separately: see, for example Mumtaz and Zanetti (2012) and prior work cited by them.

3.2 VAR Shock Identification

With posterior distributions for the values of the reduced-form VAR coefficients in hand, we can proceed to identify the risk news shocks. Consider moving average representation of the VAR(K)

$$y_t = B(L)\, u_t. \tag{3.5}$$

We proceed, as in other VAR work, under the assumption that there is some idealized mapping between the reduced-form errors estimated, and the underlying and unobserved structural shocks, and the structural shocks exists, namely

$$u_t = A\varepsilon_t, \tag{3.6}$$

such that $AA' = \Sigma$, the variance-covariance matrix of the vector of reduced-form errors ε_t. Suppose our Bayesian estimation of the reduced form for y_t delivers some $\widetilde{A}$ from which we seek to learn about the idealized A. In this case, the h step-ahead forecast error can be expressed as

$$y_{t+h} - E_{t-1}y_{t+h} = \sum_{\tau=0}^{h} B_\tau \widetilde{A} Q(\omega)\, \varepsilon_{t+h-\tau}.$$

$\tilde{A}$ is the lower triangular matrix obtained from the Cholesky decomposition of $\widetilde{\Sigma}$; Q is an orthonormal matrix formed from a product of $0.5 \times N \times (N-1)$ Givens matrices, such that $Q(\omega)\, Q(\omega)' = I_N$, where I_N is the $N \times N$ identity matrix and ω is a vector of length $0.5 \times N \times (N-1)$,with each element of ω a member of $\begin{bmatrix} 0 & 2\pi \end{bmatrix}$ corresponding to a 'rotation' angle.

The share of the forecast error variance of variable i, attributable to the structural shock j at horizon h, is written as:

$$\Omega_{i,j}(h) = \frac{e_i' \left(\sum_{\tau=0}^{h} B_\tau \widetilde{A} Q(\omega)\, e_j e_j' Q(\omega)' \widetilde{A}' B_\tau \right) e_i}{e_i' \left(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau \right) e_i}, \tag{3.7}$$

where e_i denotes the selection vector with one in the i-th place and zeros elsewhere.

Similarly to BS, and consistently with the model discussed below, we assume that cross-sectional risk is exogenous and driven by two random disturbances; a contemporaneous shock, and a news shock. An example of a process that takes this form is the following:

$$\ln \sigma_{\omega,t} = (1-\rho_\sigma)\, \sigma_\omega + \rho_\sigma \ln \sigma_{\omega,t-1} + \varepsilon_{\sigma_\omega,t} + \varepsilon_{t-1}^{news}. \tag{3.8}$$

Where the contemporaneous shock is denoted $\varepsilon_{\sigma_\omega,t}$ and the news shock is labelled $\eta_{news,t-1}$. Note that this is exactly the process assumed for the risk shock in the DSGE Monte Carlo and DSGE estimation exercises that we conduct and report on below. But for now this is just an example of a process that would be consistent with the VAR identification. This identification requires just that risk is driven by its own lags (of which there could be many), a contemporaneous shock, and news shocks, of which there could be many (i.e. shocks crystallizing announcements that were made at several different horizons before time t, not just the one horizon $t-1$ in the example process above).

By allowing $\varepsilon_{\sigma_\omega,t}$ to be the first element of ε and ε_{t-1}^{news} the second, then, by assumption we get that

$$\Omega_{1,1}(h) + \Omega_{1,2}(h) = 1. \tag{3.9}$$

However, it is unlikely that condition (3.9) holds at all horizons exactly in a multivariate VAR model with real data. Hence, as suggested by BS, we select the second column of the (rotated) impact matrix – $\widetilde{A}Q(\omega)$ – that comes as close as possible to making equation (3.9) hold over a finite set of horizons.

Since we intend to identify additional, more familiar – technology, demand, monetary policy – shocks, and also wish to be able to impose that the responses to the risk news shock satisfy certain qualitative restrictions, we combine BS's method with sign restrictions, following Uhlig (2005), Canova and De Nicolo (2002) and others.

To be precise, we find the vector of angles ω that maximizes the forecast error variance associated with the column of the impact matrix $\tilde{A}Q(\omega)$, while satisfying the sign restrictions implied by other structural shocks. In algebraic term the problem is stated as follows:

$$\omega^* = \arg\max \sum_{h=0}^{H} \Omega_{i,j}(h) = \arg\max \sum_{h=0}^{H} \frac{e_i'\left(\sum_{\tau=0}^{h} B_\tau \widetilde{A}Q(\omega) e_j e_j' Q(\omega)' \widetilde{A}' B_\tau\right) e_i}{e_i'\left(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau\right) e_i}, \tag{3.10}$$

subject to

$$\widetilde{A}(1,j) = 0, \tag{3.11}$$

where $j > 1$.

$$sign(SA_{22}) = F \text{ or } sign(SA_{22}) = -F \tag{3.12}$$

where S is a selector matrix that has 1s in elements corresponding to restricted elements, and 0s elsewhere, $sign$ refers to the signum function, which maps real positive elements to 1s, and real negatives to -1s, F is a matrix that has -1s where the IRF is restricted to be negative, 1s for elements restricted to be positive, and 0s elsewhere, and $\widetilde{A}_{22}$ is a 9×9 submatrix of $\widetilde{A}$ defined in the conventional way.

$$Q(\omega)\,Q(\omega)' = I, \tag{3.13}$$

where I is the 10×10 identity matrix, and $Q(\omega) = Q(\omega_1) \times Q(\omega_2) \times ... \times Q(\omega_9)$, ω_n refers to the scalar members of the vector of angles, ω, and Q is a 9×9 Givens matrix, constructed in a standard fashion. Constraint (3.11) implies that only the contemporaneous risk shock has a contemporaneous effect on the risk proxy. Constraint (3.12) ensures that ω^* satisfies the sign restrictions associated the structural shocks.

By ordering the risk proxy first in the VAR, $\widetilde{A}$, Cholesky factor of $\widetilde{\Sigma}$, can be written thus:

$$\widetilde{A} = \begin{bmatrix} \sigma_\sigma & 0 \\ \widetilde{A}_{2,1} & \widetilde{A}_{2,2} \end{bmatrix}. \tag{3.14}$$

With the risk shock σ_ω appearing in the upper left hand element. (By assumption, in this particular row of the VAR the structural shock equals the reduced-form shock.) Next we select ω^* so the rotation matrix $Q_{2,2}(\omega^*)$ satisfies the sign restrictions for $A_{2,2}$. Noting that $Q(\omega^*)$ can be written as follows:

$$Q(\omega^*) = \begin{bmatrix} 1 & 0 \\ 0 & Q_{2,2}(\omega^*) \end{bmatrix}, \tag{3.15}$$

it is not hard to see that $Q(\omega^*)$ satisfies both (3.12) and (3.13).

Table 1 summarizes the sign restrictions that we use to identify the structural shocks.

Table 1: Sign-Restrictions

	t				$t+1$			
VAR	News	Supply	Demand	Policy	News	Supply	Demand	Policy
Uncertainty	0	0	0	0	+			
Spread								
GDP Growth	-	+	+	-	-	+	+	-
Consumption Growth								
Investment Growth								
Hours								
Wage Growth								
Inflation	-	-	+	-	-	-	+	-
Policy Rate	-	-	+	+	-	-	+	+
Net Worth Growth	-	+	+	-	-	-	+	-

In words, a positive technology shock increases output on impact, increases net worth, but decreases inflation and interest rates; a positive innovation to demand (which could, perhaps, capture a change in the degree of impatience in a DSGE model, or a shock to fiscal policy) raises output, inflation and interest rates; a contractionary monetary policy shock raises interest rates on impact, lowering output and inflation. The same restrictions are also imposed in $t+1$. We also impose sign restrictions on the risk news shock, that revelation about an increase in cross-sectional risk in the future lowers GDP growth, inflation, the growth in net worth, and this despite also prompting the central bank to cut rates. These restrictions are consistent with plausible parameterizations of the SW+BGG model that we will deploy later in the paper, and also with CMR.

3.3 Data

The information set consists of seven macroeconomic and three financial quarterly US data series over a sample period running from 1980Q1 to 2010Q2. The seven macroeconomic variables are those used by Smets and Wouters (2007): the log difference of real GDP, real consumption, real gross investment, real wage and the GDP deflator; the log of hours worked; and the federal funds rate. The financial series comprise: the difference between BBA and AAA corporate bond yields (a measure for the external finance premium in BGG), the per capita Dow Jones Wilshire index deflated by the GDP deflator as in CMR (a proxy for entrepreneurial net worth) and a proxy for risk. We experiment with two proxies for the time series of idiosyncratic uncertainty faced by entrepreneurs in the private sector. In our benchmark results, we use the VIX, a popular measure of uncertainty, derived from implied volatilities on the S&P 500 index options.[2] However, since this is a potentially contestable measure

[2]Recent papers show (along with us here) that there is a close empirical and theoretical relationship between the volatility of various asset classes and the cross-sectional dispersion within given asset classes. See for example, Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) and Cesa-Bianchi, Pesaran, and Rebucci (2013). Moreover, in the structural model presented in the next section option implied volatility is constant so any variations must be caused by exogenous perturbations.

of cross-sectional risk, to check for the robustness of our results we use, as an alternative measure, the interquartile range of the cross section of stock returns in the US produced by Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012).[3]

3.4 VAR Results

Chart 2 presents the impulse responses to the identified risk news shock where our chosen value for h, the horizon up to which the risk news shock is constructed to explain the maximum proportion of forecast error variance in the risk proxy is 4 quarters (we discuss robustness to alternative choices later). Note that all the shocks have been scaled to deliver a 0.25pp fall in GDP growth (per quarter) on impact. The VAR has 3 lags, following Smets and Wouters (2007). Results are little changed, however, for models with 1,2 and 4 lags.[4] The black lines and shaded areas in the chart require some explanation, and this will serve to reveal the details of the algorithm used to carry out the identification. The chart plots a distribution formed by the following: i) we take 1000 draws from the estimated posterior distribution for the reduced-form VAR estimates, ii) for each, we find 1000 rotations of the VAR's residual variance-covariance matrix that satisfy our sign and zero restrictions, iii) we search across them to find the rotation that maximizes the forecast error variance criterion (expression (3.10)), giving us 1000 preliminary estimates of 'maxima' corresponding to the 1000 VARs in the posterior, iv) we use this as an input to MATLAB's fminsearch to find a better estimate of the maximum in each case (i.e. we get 1000 refined estimates of the maximum). Then the black line in chart 2 below is constructed from the pointwise median of these 1000 maxima and the 32nd and 68th percentiles formed analogously.[5]

Our volatility proxy (in this benchmark case, the VIX), peaks somewhat *after* the first period, by construction (the risk news shock, since it is news about future risk, has to be orthogonal to risk in the initial period). The VIX risk proxy remains above steady state for almost 3 years.[6] A risk news shock large enough to cause the VIX risk proxy to rise by almost $4.5pp$ (compared to the 40pp rise seen at the start of the financial crisis), causes spreads to rise by 5 basis points (compared to 50bp rise seen at the start of the financial crisis), and this in turn leads to a persistent fall in investment (maximum impact -2%) and to a relatively transitory drop in consumption (of about $-0.4pp$). As a consequence GDP contracts ($-0.25pp$, in this case both sign and scale are by construction) and weak demand is translated into low hours (which fall by 1%) and inflation (which falls (by construction) by 0.4pp). Consistent with the rise in spreads and lower investment, net worth drops (sign by construction) by $4pp$. These falls are despite the monetary authority cutting rates aggressively and for a protracted period (the cut is by construction, the scale freely estimated).

Chart 8 compares the impulse responses to the contemporaneous risk and risk news shocks. The two are compared by taking the profile for VIX that is induced by a risk news shock, replicating this with

[3]This measure is downloadable from Nick Bloom's website.

[4]These results are available upon request.

[5]By 'pointwise' we mean that at each horizon h we find the median of the impulse responses, and display a black dot, and the black line is constructed by joining the black dots corresponding to each h; analogously for other percentiles, a usage of 'pointwise' that conforms to others in the VAR literature. To re-emphasize, the medians and bands do *not* correspond to the objects reported by researchers who use sign restrictions only in VARs. The sets of rotations that satisfy those restrictions and are plotted by those researchers are here reduced to single lines by the maximising step in the BS identification scheme.

[6]Note that the peak of the impulse of the volatility proxy to the news shock does not have to coincide with the $h = 4$ chosen for the maximisation of the forecast variance contribution.

a matching sequence of contemporaneous risk shocks. From this chart we can see that the one of risk news shock induces a larger shift in spreads, output, consumption, investment, inflation and policy rates.[7]

Charts 3, 4 and 5 plot the impulse responses to the technology, demand and monetary policy shocks. The magnitude and shape of these look reasonable (remember many of the *signs* are restricted in identification). Noteworthy is that spreads move very little (insofar as the VAR can tell - all are somewhat ill-determined) in response to these shocks. One can take this as echoing the result from other work in business cycle models that the financial accelerator does not amplify traditional shocks that much. If it did, such amplification would show up first via large movements in spreads (or at least this is what BGG and related models would predict).

The first headline of our analysis can be seen in Chart 7 which shows the forecast error variance decomposition [FEVD] (for the 9 'endogenous' series, i.e. excluding the risk proxy; recall that we are identifying the risk news shocks by maximizing the contribution to future movements of the risk proxy). Looking at the panel for output, we can see that the risk news shock explains about 10% of long-run fluctuations. Taken together with the contemporaneous risk shock, the contribution is about 20%. CMR, by contrast, find that the contribution of the risk news shock alone is 38%, and the combined contribution of this shock and the contemporaneous risk shock is 60%. We should not deduce from this that the shocks are not a significant part of the story of the US, however. Note first that they contribute about 20% of the volatility in spreads, 30% of the volatility in inflation. Interestingly, the 'policy rates' panel in Chart 7 shows that the risk news shock contributes almost 40% to fluctuations in the central bank instrument. So risk news shocks contribute little to output growth, but partly because the central bank acts to respond to them vigorously and insulate the macroeconomy from their effects. We might conjecture that with interest rates pinned to the zero bound, revelations about future changes in uncertainty would therefore be contributing more, at least to the extent that unconventional policy instruments fail to substitute adequately for the missing interest rate stimulus.

Before we go on, our punchline chart showing the forecast error variance decomposition requires some explanation. Since there are actually many VARs estimated and reported earlier, which FEVD have we chosen? Recapping on the text above, we have 1000 posterior draws for the VAR parameters, and each one generates a maximum corresponding to the output of the BS part of the procedure. For each of these 1000 VARs, we can report a FEVD at each horizon, call this, say, H_t which will have 2 dimensions, corresponding to shocks and observables. What we report is the single H corresponding to the single VAR whose H lies closest to the median H_t at each t, where the distance is calculating using the Euclidian norm (the dimension of the corresponding space given by the 10(shocks)$\times$ 10(observables)).

This explanation hopefully makes it clear that there is, in fact, a distribution of possible Hs, expressing the estimation uncertainty inherent in our VAR exercise. Our headline 20% number is a central estimate. To this end, we illustrate the uncertainty around it in Chart 12. To this end, one can see that we can say that our results put a posterior probability of 68% on the event that the combined contribution of the risk and risk news shocks lies between 10% and 40%.

Chart 6 provides the historical decomposition of the VAR series over the recent past, 2006Q1-2010Q2,

[7] The differences in the magnitude of the responses relative to Chart 2 are because we do not scale the shock to deliver 0.25% drop in GDP.

using an analogous procedure to that for the construction of Figure 7. This chart measures what the VAR estimates to be the contribution to the values of the time series from each of the identified shocks.

In the reported decomposition, the contributions of the shocks that have not been identified (recall we identify just risk, risk news, monetary policy, technology, demand, leaving 5 unidentified) are added together in one (yellow) bar labelled 'residuals'. It is clear from Chart 6 that the VAR deduces that risk news shocks had quite a role to play in the crisis, pushing up on spreads, and accounting for about a third of the fall in consumption and investment growth relative to trend. These shocks do not appear to contribute much to the fall in output, however, suggesting perhaps that systematic fiscal policy was at work (G is obviously part of the gap between Y and C+I).

Notwithstanding the role our VAR infers that central banks had, our alternative method for isolating the contribution of risk news shocks indicates that this shock winds up contributing much less to business cycle volatility in output than in CMR. It is incumbent on us to show that this result does not depend overly on the VIX as our risk proxy.

3.4.1 Robustness to Using an Alternative Measure of Cross-sectional Risk

To this end, we redo the entire analysis up to this point using a measure of the interquartile range of the cross section of stock returns from US firms derived by Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012).[8] Chart 9 plots this new risk proxy against the VIX and illustrates that the two measure are very similar with the correlation coefficient being 0.75.

Chart 13 compares the impulse responses in the VAR with the cross section of returns measure to the VAR estimated with the VIX. The results suggest that the risk news shock in the cross-section returns VAR induces very similar impulses to our observables, with the exception that the risk proxy itself rises a lot more in the future.

Chart 10 reports the forecast error variance decomposition using the cross-section measure. In this case we see that the contribution of the risk news shock (and also the technology shock and the monetary policy shock) are very small, around 2%. Though the contribution of the contemporaneous risk shock amounts to about 20% (roughly the same contribution as demand shocks). If we sum the contributions of the risk and the risk news shocks, then for both VARs (i.e. for the 2 risk proxies) the sum is in the region of 20%. In this sense the VARs give reasonably similar answers, although they divide up that 20% between the two shocks quite differently.

3.4.2 Robustness to Using Alternative Values for h, the Horizon in the 'max share' Criterion

Recall that one dimension of the identification procedure is the horizon h; this refers to the horizon in quarters up to which we try to maximize the contribution of the risk news shock to fluctuations in the risk proxy. Chart 11 shows what happens when we choose alternative values for h, recalling that

[8] This measure is downloadable from Nick Bloom's website. The interquartile range is thought to be a more robust estimator of dispersion than the standard deviation when data (particularly in the tails of the distribution of returns) are measured with error. In the absence of measurement error, and if the distribution of returns were normal, the interquartile range will equal the standard deviation.

our benchmark value was 4 quarters. The chart plots the contributions at various horizons of both the contemporaneous and risk news shocks, for $h = 12, 40$ as well as our initial base case of $h = 4$. In either case, the combined contributions of the two shocks to the long horizon volatility in output growth are no more than 20%, and in fact substantially less.

4 DSGE Model with Financial Frictions

We move on, and set out a DSGE model with financial frictions that encodes risk and risk news shocks of the type we have looked to identify in the VAR. We use the DSGE model to do two things. First, we estimate the model using minimum distance methods, choosing the model's parameters to bring the impulse response to a risk news shock as close as possible to that identified in the VAR. Second, we use the model as a laboratory to conduct a Monte Carlo test to evaluate the accuracy with which the VAR identification method uncovers the true shocks and corresponding impulse responses. (Note that we have already invoked the DSGE model to some extent in motivating the sign restrictions placed on the risk news and other shocks.)

The next subsection briefly discusses the linearized first order conditions that results from agents' decision problems. The model is essentially Smets and Wouters (2007) (which in turn was a close relative of CEE) modified to include financial frictions as in BGG. The model features risk-averse consumers who supply labour to differentiated and sticky wage labour unions. There are risk-neutral entrepreneurs who borrow from perfectly competitive banks, build capital goods that they rent to the imperfectly competitive (sticky price) producers of intermediate goods producers. And there are the familiar perfectly competitive retailers selling the aggregated intermediate goods as a composite final good to the consumers. There is a government (following a simple debt-targeting rule) and a central bank (setting monetary policy according to a Taylor-like rule). The model features many frictions: habits in consumption, price and wage stickiness as in Calvo (1983) and also price and wage indexation as in Smets and Wouters (2007) and CEE. As in BGG, there is an informational friction between banks and entrepreneurs who construct capital goods for use by the intermediate goods producers. Following the literature, the optimal debt contract implies that banks charging a spread over the policy rate (also their retail deposit rate) to the entrepreneurs which is a function of entrepreneurs' net worth. Finally, (following Gali, Lopez-Salido, and Valles (2007) and Cogan, Cwik, Taylor, and Wieland (2010)), we allow for there to be a certain portion of households who do not have access to financial markets and cannot therefore smooth consumption. These rule-of-thumb (ROT) households simply consume all their labour income (and a transfer that equates the steady-state consumption between non-optimizing and optimizing agents). As we shall see, we can get the DSGE model to fit the VARs impulse responses to the risk news shock, but only by allowing for 75% of consumers to to of ROT type.

4.1 Linearized First Order Conditions of the DSGE model

All the variables are expressed as log deviations from their steady-state values. $\mathbb{E}_t$ denotes expectation formed at time t, '$-$' denotes the steady state values, and all the shocks (η_t^i) are assumed to be normally distributed with zero mean and unit standard deviation.

The demand side of the economy consists of consumption (c_t), investment (i_t), capital utilization (z_t) and government spending $\left(\varepsilon_t^g = \rho_g \varepsilon_{t-1}^g + \sigma_g \eta_t^g\right)$, which is assumed to be exogenous. The market clearing condition is given by

$$
\begin{aligned}
y_t &= c_y c_t + i_y i_t + z_y z_t + \varepsilon_t^g \qquad (4.1)\\
&+ \frac{\mu}{\bar{\pi}\gamma} G\left(\bar{\omega}, \sigma_\omega\right) \bar{R}^k \frac{\bar{K}}{\bar{Y}} \left(R_t^k + q_{t-1} + k_{t-1} + \frac{\frac{\partial G(\bar{\omega},\sigma_\omega)}{\partial \omega}}{G\left(\bar{\omega}, \sigma_\omega\right)} \bar{\omega} \omega_t + \frac{\frac{\partial G(\bar{\omega},\sigma_\omega)}{\partial \sigma_\omega}}{G\left(\bar{\omega}, \sigma_\omega\right)} \sigma_\omega \sigma_{\omega,t} \right),
\end{aligned}
$$

where y_t denotes the total output and Table (2) provides a full description of the model's parameters. The last term in equation (4.1) captures the cost of financial frictions in the the economy, where R_t^k stands for the return on capital, q_t is the real value of existing capital stock (Tobin's Q), k_t is the stock of physical capital, ω_t is the cutoff value that divides bankrupt from non bankrupt entrepreneurs and $\sigma_{\omega,t}$ denotes the standard deviation of the entrepreneur's idiosyncratic productivity shock.[9] We follow the literature (CMR) and we refer to this process as the 'risk shock', which captures the idea that the riskiness of the entrepreneurs varies over time. The law of motion for $\sigma_{\omega,t}$ is specified as follows

$$
\sigma_{\omega,t} = \rho_{1,\sigma} \sigma_{\omega,t-1} + \rho_{2,\sigma} \sigma_{\omega,t-2} + \rho_{3,\sigma} \sigma_{\omega,t-3} + \sigma_{\sigma_\omega} \eta_t^\omega + \varkappa_{t-1}, \qquad (4.2)
$$

and the news term, $\varkappa_t$, evolves according to

$$
\varkappa_t = \sigma_\varkappa \eta_t^\varkappa. \qquad (4.3)
$$

It can be easily seen that by setting the auditing cost parameter (μ) equal to zero (no asymmetry between lenders and borrowers and, consequently, no financial frictions), the latter expression collapses to the standard market clearing condition. Finally, it should be noted that aggregated consumption is the weighted sum of consumption of the optimizing $\left(c_t^{opt}\right)$ and ROT $\left(c_t^{RoT}\right)$ households

$$
c_t = \phi_{RoT} c_t^{RoT} + \left(1 - \phi_{RoT}\right) c_t^{opt}. \qquad (4.4)
$$

The consumption Euler equation for optimizing consumers is given by

$$
\begin{aligned}
c_t^{opt} &= \frac{\lambda/\gamma}{1+\lambda/\gamma} c_{t-1}^{opt} + \left(1 - \frac{\lambda/\gamma}{1+\lambda/\gamma}\right) \mathbb{E}_t c_{t+1}^{opt} + \frac{\left(\sigma_C - 1\right)\left(\bar{W}^h \bar{L}/\bar{C}\right)}{\sigma_C\left(1+\lambda/\gamma\right)} \left(l_t - \mathbb{E}_t l_{t+1}\right)\\
&- \frac{1-\lambda/\gamma}{\sigma_C\left(1+\lambda/\gamma\right)} \left(r_t - \mathbb{E}_t \pi_{t+1}\right) + \varepsilon_t^b, \qquad (4.5)
\end{aligned}
$$

where l_t is the hours worked, r_t is the nominal interest rate, π_t is the rate of inflation and $\varepsilon_t^b = \rho_b \varepsilon_{t-1}^b + \sigma_b \eta_t^b$ is a consumption preference shock. If the degree of habits is zero ($\lambda = 0$), equation (4.5) reduces to the standard, forward-looking consumption Euler equation. The linearized investment equation is given by

$$
i_t = \frac{1}{1+\beta\gamma^{1-\sigma_C}} i_{t-1} + \left(1 - \frac{1}{1+\beta\gamma^{1-\sigma_C}}\right) \mathbb{E}_t i_{t+1} + \frac{1}{\left(1+\beta\gamma^{1-\sigma_C}\right)\gamma^2 \varphi} q_t + \varepsilon_t^i, \qquad (4.6)
$$

where i_t denotes investment and $\varepsilon_t^i = \rho_i \varepsilon_{t-1}^i + \sigma_i \eta_t^i$ is an investment efficiency shock. The sensitivity of

[9] $G\left(\bar{\omega}, \sigma_\omega\right) = 1 - \Phi\left(\frac{0.5\sigma_\omega - log\bar{\omega}}{\sigma_\omega}\right)$, where Φ is the CDF of a normal distribution and $\frac{\partial G(\bar{\omega},\sigma_\omega)}{\partial \sigma_\omega}$ denotes the partial derivative of $G\left(\bar{\omega}, \sigma_\omega\right)$ with respect to σ_ω.

investment to the real value of the existing capital stock depends on the parameter φ (see, Christiano, Eichenbaum, and Evans, 2005). The demand curve for new capital is given by

$$R_t^k = \pi_t + \frac{\bar{\pi}\bar{r}^k}{\bar{R}^k}\left(r_t^k + z_t\right) + \frac{(1-\delta)\,\bar{\pi}}{\bar{R}^k} q_t - q_{t-1}, \tag{4.7}$$

where $r_t^k = -(k_t - l_t) + w_t$ denotes the real rental rate of capital which is negatively related to the capital-labour ratio and positively to the real wage. Capital utilization, on the other hand, is proportional to the real rental rate of capital, $z_t = \frac{1-\psi}{\psi} r_t^k$.

On the supply side of the economy, the aggregate production function is defined as

$$y_t = \phi_p \left(\alpha k_t^s + (1-\alpha)\, l_t + \varepsilon_t^a\right), \tag{4.8}$$

where k_t^s represents capital services which is a linear function of lagged installed capital (k_{t-1}) and the degree of capital utilization, $k_t^s = k_{t-1} + z_t$, and $\varepsilon_t^a = \rho_a \varepsilon_{t-1}^a + \sigma_a \eta_t^a$ is a stationary productivity shock. The accumulation process of installed capital is simply described as

$$k_t = \frac{1-\delta}{\gamma} k_{t-1} + \frac{\gamma - 1 + \delta}{\gamma}\left(i_t + \gamma^2 \varphi \varepsilon_t^i\right). \tag{4.9}$$

Monopolistic competition within the production sector and Calvo-pricing constraints gives the following New Keynesian Phillips curve for inflation (when combined with the definition of the aggregate price index):

$$\begin{aligned} \pi_t = {} & \frac{i_p}{1+\beta\gamma^{1-\sigma_C} i_p}\pi_{t-1} + \frac{\beta\gamma^{1-\sigma_C}}{1+\beta\gamma^{1-\sigma_C} i_p}\mathbb{E}_t \pi_{t+1} \\ & - \frac{1}{\left(1+\beta\gamma^{1-\sigma_C} i_p\right)} \frac{\left(1-\beta\gamma^{1-\sigma_C}\xi_p\right)\left(1-\xi_p\right)}{\left(\xi_p\left(\left(\phi_p - 1\right)\varepsilon_p + 1\right)\right)} \mu_t^p + \varepsilon_t^p, \end{aligned} \tag{4.10}$$

where $\mu_t^p = \alpha\left(k_t^s - l_t\right) + \varepsilon_t^a - w_t$ is the marginal cost of production and $\varepsilon_t^p = \rho_p \varepsilon_{t-1}^p + \sigma_p \eta_t^p - \mu_p \sigma_p \eta_{t-1}^p$ is a price mark-up shock, which is assumed to follow an ARMA(1,1) process. Monopolistic competition in the labour market gives rise to a similar New Keynesian Phillips curve for nominal wages

$$\begin{aligned} w_t = {} & \frac{1}{1+\beta\gamma^{1-\sigma_C}} w_{t-1} + \frac{\beta\gamma^{1-\sigma_C}}{1+\beta\gamma^{1-\sigma_C}}\left(\mathbb{E}_t w_{t+1} + \mathbb{E}_t \pi_{t+1}\right) - \frac{1+\beta\gamma^{1-\sigma_C} i_w}{1+\beta\gamma^{1-\sigma_C}}\pi_t \\ & + \frac{i_w}{1+\beta\gamma^{1-\sigma_C}}\pi_{t-1} - \frac{1}{1+\beta\gamma^{1-\sigma_C}} \frac{\left(1-\beta\gamma^{1-\sigma_C}\xi_w\right)\left(1-\xi_w\right)}{\left(\xi_w\left(\left(\phi_w - 1\right)\varepsilon_w + 1\right)\right)} \mu_t^w + \varepsilon_t^w, \end{aligned} \tag{4.11}$$

where $\mu_t^w = w_t - \left(\sigma_l l_t + \frac{1}{1-\lambda/\gamma}\left(c_t - \lambda/\gamma c_{t-1}\right)\right)$ is the households' marginal benefit of supplying an extra unit of labour service and the wage mark-up shock $\varepsilon_t^w = \rho_w \varepsilon_{t-1}^w + \sigma_w \eta_t^w - \mu_w \sigma_w \eta_{t-1}^w$ is also assumed to be an ARMA(1,1) process.

Loans (B_t) to entrepreneurs are defined as

$$B_t = \frac{\bar{K}}{\bar{B}}\left(q_t + k_t\right) - \frac{\bar{K} - \bar{B}}{\bar{B}} n_t, \tag{4.12}$$

where n_t stands for the entrepreneurs' net worth. The following two equations are the linearized entrepreneurs' first order conditions with respect to the Lagrange multiplier and leverage, respectively:

$$B_t = R_t^k - r_{t-1} + q_{t-1} + k_{t-1} + \frac{1}{\Gamma(\bar{\omega}, \bar{\sigma}_\omega) - \mu G(\bar{\omega}, \sigma_\omega)} \begin{pmatrix} \frac{\partial[\Gamma(\bar{\omega},\sigma_\omega) - \mu G(\bar{\omega},\sigma_\omega)]}{\partial\omega} \bar{\omega}\omega_t \\ + \frac{\partial[\Gamma(\bar{\omega},\bar{\sigma}_\omega) - \mu G(\bar{\omega},\sigma_\omega)]}{\partial\sigma_\omega} \sigma_\omega \sigma_{\omega,t} \end{pmatrix}, \tag{4.13}$$

$$E_t R_{t+1}^k = r_t + \left(\frac{\frac{\partial\varrho(\bar{\omega},\sigma_\omega)}{\partial\omega}}{\varrho(\bar{\omega},\sigma_\omega)} + \frac{\frac{\partial\Gamma(\bar{\omega},\sigma_\omega)}{\partial\omega}}{1 - \Gamma(\bar{\omega},\sigma_\omega)} \right) \bar{\omega}\omega_{t+1} + \left(\frac{\frac{\partial\varrho(\bar{\omega},\bar{\sigma}_\omega)}{\partial\sigma_\omega}}{\varrho(\bar{\omega},\bar{\sigma}_\omega)} + \frac{\frac{\partial\Gamma(\bar{\omega},\sigma_\omega)}{\partial\sigma_\omega}}{1 - \Gamma(\bar{\omega},\sigma_\omega)} \right) \sigma_\omega \sigma_{\omega,t+1} + n_t - q_t - k_t, \tag{4.14}$$

where r_t is the nominal interest rate and

$$\Gamma(\bar{\omega}, \bar{\sigma}_\omega) = \bar{\omega}(1 - F(\bar{\omega}, \sigma_\omega)) + G(\bar{\omega}, \sigma_\omega), \tag{4.15}$$

$$\varrho(\bar{\omega}, \bar{\sigma}_\omega) = \frac{1 - F(\bar{\omega}, \sigma_\omega)}{1 - F(\bar{\omega}, \sigma_\omega) - \mu\bar{\omega}\frac{\partial F(\bar{\omega},\sigma_\omega)}{\partial\omega}}, \tag{4.16}$$

where $F(\bar{\omega}, \sigma_\omega)$ denotes the probability of default. The evolution the net worth is given by:

$$n_t = \frac{\bar{\varsigma}}{\gamma\bar{\pi}} \left(\frac{(1 - \mu G(\bar{\omega}, \sigma_\omega))\bar{R}^k}{1 - \frac{\bar{B}}{\bar{K}}} - \frac{\bar{r}\frac{\bar{B}}{\bar{K}}}{1 - \frac{\bar{B}}{\bar{K}}} \right) \varsigma_t + \frac{\bar{\varsigma}}{\gamma\bar{\pi}} \frac{(1 - \mu G(\bar{\omega}, \sigma_\omega))\bar{R}^k}{1 - \frac{\bar{B}}{\bar{K}}} \left(R_t^k + q_{t-1} + k_{t-1} \right) - \frac{\bar{\varsigma}}{\gamma\bar{\pi}} \frac{\bar{R}\frac{\bar{B}}{\bar{K}}}{1 - \frac{\bar{B}}{\bar{K}}} (r_{t-1} + B_{t-1}) - \frac{\bar{\varsigma}}{\gamma\bar{\pi}} \frac{\mu\bar{R}^k}{1 - \frac{\bar{B}}{\bar{K}}} \left(\frac{\partial G(\bar{\omega}, \sigma_\omega)}{\partial\omega} \omega\omega_t + \frac{\partial G(\bar{\omega}, \sigma_\omega)}{\partial\sigma_\omega} \sigma_\omega\sigma_{\omega,t} \right), \tag{4.17}$$

where $\varsigma_t = \rho_\varsigma \varsigma_{t-1} + \sigma_\varsigma \eta_t^\varsigma$ is the fraction of the entrepreneurs that die each period. The consumption of non-optimizing, ROT agents is given by:

$$c_t^{RoT} = \frac{\bar{W}^h \bar{L}}{\bar{C}} (w_t + l_t) - \frac{\bar{Y}}{\bar{C}} trans_t. \tag{4.18}$$

The following equation describes the evolution of government debt:

$$d_t = \bar{R} \left(\frac{1}{\bar{\pi}} d_{t-1} + \varepsilon_t^g - trans_t \right). \tag{4.19}$$

Transfers are set to follow a simple debt-targeting rule given by:

$$trans_t = \phi_d d_{t-1} + \phi_g \varepsilon_t^g. \tag{4.20}$$

Finally, the monetary policy maker is assumed to set the nominal interest rate according to the following Taylor-type rule

$$r_t = \rho r_{t-1} + (1 - \rho)[r_\pi \pi_t + r_y (y_t - y_t^p)] + r_{\Delta y} \left[(y_t - y_t^p) + \left(y_{t-1} - y_{t-1}^p \right) \right] + \varepsilon_t^r, \tag{4.21}$$

where y_t^p is the flexible price level of output, and $\varepsilon_t^r = \rho_r \varepsilon_{t-1}^r + \sigma_r \eta_t^r$ is a monetary policy shock.[10]

[10] The flexible price level of output is defined as the level of output that would prevail under flexible prices and wages in the absence of the two mark-up shocks.

4.2 Minimum Distance Estimation (MDE)

Our next step is to estimate the DSGE model using limited-information methods. We started by seeking evidence - independent of any particular DSGE model - on the consequences and contribution of risk news shocks, and were led by that focus to identify such shocks in a VAR.[11] Having done that, it seems natural to see what this shock implies for a DSGE model of interest. As we shall see, the VAR impulse responses have some striking things to say about the model.

In brief, we find the vector of DSGE parameters that minimizes the distance between the VAR-implied and the DSGE estimates of the responses to the risk news shock. Such techniques have been used in DSGE estimation widely, for example by Rotemberg and Woodford (1998), Smets and Wouters (2002), Christiano, Eichenbaum, and Evans (2005) and Altig, Christiano, Eichenbaum, and Linde (2011). These methods have well documented costs and benefits relative to full information methods, which we summarize very briefly. The costs of partial information methods are the aggravation of identification issues already problematic in DSGE models, as documented in Canova and Sala (2009), and the burden of finding a convincing way to identify the shocks. As we have noted above, conditional on us having found a useful proxy for the time series of idiosyncratic risk (note that CMR use this time series to check, ex post, that their full information recovered series is a good one), the validity of the method is justified in part by the Monte Carlo exercises which show that at least in a relevant DSGE model the modified BS procedure does recover the news shocks successfully, results which we will report later in the paper. The benefits of using MDE include: robustness to problems of misspecification in the DSGE model where MDE estimates will be consistent regardless, while full information estimates will not; plus good small sample properties (see, for example, Ruge-Murcia, 2007; Theodoridis, 2011) -relative to classical full information methods.[12]

Collecting all the VAR variable responses after a risk news shock for all periods in one vector, $\widehat{\mathcal{R}}$ and doing the same for the DSGE ones, denoted $\mathcal{R}(\theta)$, where θ of course collects the DSGE parameters themselves, then we can select the structural parameter vector θ that minimizes the following norm:

$$\theta = \arg\min \left(\widehat{\mathcal{R}} - \mathcal{R}(\theta)\right)' \mathcal{W} \left(\widehat{\mathcal{R}} - \mathcal{R}(\theta)\right), \tag{4.22}$$

where $\widehat{\mathcal{R}}$ corresponds to the median of the posterior distribution of the VAR identified responses and $\mathcal{W}$ is the inverse of the diagonal matrix of the variance-covariance matrix of the posterior distribution of the VAR identified responses. This choice for $\mathcal{W}$ is common in DSGE estimation (see Christiano, Eichenbaum, and Evans (2005), Altig, Christiano, Eichenbaum, and Linde (2011)).

The model defines 34 parameters (recall that since we are fitting just the risk news shock, we are not estimating any of the other shocks defined in Smets and Wouters (2007) or BGG). Of these we calibrate 9, setting those equal to the values reported in Smets and Wouters (2007). These divide up into parameters calibrated in SW and also elsewhere largely those that are pinned down by steady states or steady-state ratios, or known to be not well identified in DSGE models, and the parameters defining the Taylor Rule. We opt not to fit the Taylor Rule parameters because there is a very mature literature on this aspect of monetary economies, with many (including full information) methods

[11] Our VARs are independent of particular parameterised DSGE models, but the identification of course rests on certain properties of classes of them, through the use of sign restrictions.

[12] Note that in our context MDE gives us robustness in particular against mis-specifying the shocks other than the risk/risk news shocks. This would provide some comfort to RBC modellers who felt that those other shocks were spurious additions to the model.

deployed to estimate it. So we adopt the position of taking what we know from elsewhere about central bank behaviour, what does the VAR's identified risk shock have to say about the other aspects of the DSGE model? Table 2 reports the values of those parameters estimated, and reports those that have been calibrated. Chart 14 plots the impulse response to a risk news shock comparing the VAR with the DSGE model at the minimum distance estimates. As we see, the DSGE model can be made to fit many of the VAR responses reasonably well, including output, consumption, investment, hours, inflation, net worth and the central bank rate.

However, there are two other points to take away from the results. First, our MDE results suggest that the portion of ROT consumers amounts to 75%. Without this, we cannot match the fall in consumption that the VAR estimates follows the risk news shock. In the DSGE model, a vigorous and protracted fall in the policy rate causes rational consumers to bring consumption forward. As explained in CMR the wealth-like effect of the revelation of higher future risk that depresses consumption is relatively weak, and not sufficient to offset the substitution effect generated by the looser monetary policy. The MDE results imply a high proportion of ROT consumers to turn off a good deal of this intertemporal consumption substitution by rational consumers, thus dampening the transmission of the loose monetary policy. The contrasting responses of the model with and without ROT consumers are illustrated by Charts 16 and 17. Here we plot the responses to a risk news shock for two versions of the DSGE model: one with the estimated 75% of ROT consumers, and one with 100% 'rational' or unconstrained, with all other parameters at the calibrated/minimum distance estimated values reported in Table 2. The charts show how different having a large portion of ROT consumers makes the responses of the DSGE model, and confirm that only with the 75% hand to mouth consumers does the risk news shock lead to a fall in output and consumption. In addition, the model with ROT agents generates much larger falls in hours worked and inflation. This is despite the much larger cut in the central bank interest rate. All this said, it is important to recognize that the linearized DSGE model we work with here rules out factors like precautionary saving. What the MDE interprets as ROT behaviour could point to this and other omitted features of the model.

The second point to bring out of the DSGE estimation is that the model cannot get near the implied subsequent response of the risk proxy itself or the spread to the risk news shock. This is a manifestation of the fact that the estimated standard deviation of the risk news shock is some 4 times greater than that in the VAR. Put another way, the comparison of the DSGE and VAR responses reveals that we really need a much larger shift in risk (or rather revelation of such a shift in the future) in the DSGE model to generate the same effects in the real economy as estimated in the VAR. The DSGE model propagates risk news shocks more weakly than does the VAR, and the MDE algorithm therefore achieves a match to the impulse responses by assigning large values to the standard deviation of these shocks.

We judge a key factor behind this weak propagation to be the estimated value for μ, the cost of auditing on bankruptcy, which, as can be seen from 2 is 0.05 (i.e. 5%). The lower this cost, the more we weaken the financial accelerator mechanism in the model, and the closer the model becomes to one without financial frictions, in which fluctuations in risk, and revelations about future such fluctuations, have no effect on anything else (recall that we are using a linearized DSGE model). In Chart 18, we report the results of re-estimating the model by instead calibrating μ to two other values. Other parameters that were previously estimated are estimated again; parameters that were previously calibrated are calibrated again at the same values. $\mu = 0.12$ is the value calibrated by BGG for the auditing cost.

Estimates for the remaining (free) parameters shrink the estimated variance of the shocks, as can be seen by the fact that the impulse response of the risk series (labelled 'volatility' in the Chart) shrinks towards the VAR estimated response, leaving the performance of the other impulse responses (how far they lie from the VAR responses) virtually unchanged. Calibrating at $\mu = 0.215$, the value estimated by CMR, shrinks the variance of the estimated risk news shocks further.

Readers who are sceptical that our MDE procedure could deliver estimates of μ better than those calibrated from micro-data might wonder what calibrating would do to the implied estimates of the proportion of ROT consumers. Using the CMR value for μ we get that this proportion is still 0.75. The BGG calibration for μ delivers a value of 0.5. So the qualitative result that we need a large proportion of hand-to-mouth consumers survives this experimentation. Qualitatively, at least, therefore, our conclusions about the type of DSGE model suggested by the estimated VAR impulse responses to the identified risk news shock are robust to dropping the μ that results from our MDE procedure, and using instead other calibrated values that suggest a stronger financial accelerator.

5 Monte Carlo Test of the VAR Identification Strategy

The force of our results about the contribution of risk and risk news shocks to the business cycle, and what the impulse responses to these shocks say about candidate DSGE models that can explain them rests on how well the modified BS identification scheme manages to recover risk news shocks in the first place.

In this final section we report the results of a Monte Carlo exercise to test the ability of the VAR identification strategy to recover the news shock and the estimated impulse responses. We take the DSGE model at the minimum distance estimated/calibrated values of parameters reported in Table 2 as the data generating process. We simulate 1000 different data sets with 120 observations each, corresponding to the sample size in our estimation on real data.

Figure 15 shows the impulse responses of the key macroeconomic variables following an anticipated risk news shock. Impulse responses from both the empirical VAR and the simulated VAR are shown. The performance of the VAR looks to be very good indeed. All the estimated impulses responses are within the simulation bands of the theoretical impulse responses. We interpret these results as a confirmation that our empirical approach is successful in identifying a risk news shock in the laboratory setting. These corroborate the finding of BS that their original scheme was able to recover news shocks to TFP in data generated from an RBC model.[13] That our modified scheme works well in our context seems to be very robust to different choices of h. Of course, at risk of stating the obvious, how much this evidence bears on the success or otherwise of our identification scheme in recovering the risk news shock in real data depends on how closely the real DGP resembles the DSGE laboratory we chose.

6 Conclusion

This paper takes as its starting point recent work by Christiano, Motto, and Rostagno (2013) (CMR). They built a DSGE model with financial frictions that articulated a role for contemporaneous and

[13] In the NBER working paper version BS use a sticky price RBC model and find that their method also succeeds in recovering the news shocks.

news shocks to risk. They estimated this model using full information methods and deduced that contemporaneous and risk news shocks together contributed by about 60% to business cycle fluctuations in output in the US. That this new shock turns out to be a dominant driver of business cycles deserves scrutiny, and this is what we set out to do in this paper. We take a different but complementary approach to isolating the same shocks and quantifying their contribution. We identify risk and risk news shocks in a VAR. To do this, we take two proxies for the time series of private sector risk (the VIX, and the interquartile range of US corporate stock returns). The identification strategy we use combines Barsky and Sims (2011)'s (BS) method for identifying news shocks together with sign restrictions which enable us to identify monetary policy, technology and demand shocks at the same time, and also to impose consitency between the DSGE and VAR impulse responses to the risk news shock. This modification is straightforward, and may have other interesting applications too.

In our VAR, a risk news shock is an object that is orthogonal to the risk proxy today, but contributes maximally up to some finite horizon in the future, also satisfying some sign restrictions. We find that revelations about future increases in risk cause the growth of output, consumption, investment and the level of hours worked and inflation all to fall substantially, despite a vigorous and protracted cut in central bank interest rates, and is associated with a rise in spreads. We find that the contribution of risk news shocks to business cycle fluctuations in US output is somewhere between 2 and 12%, depending on which proxy we use. The contribution of risk and risk news shocks combined is in the region of 20% regardless of which proxy we use. This combined contribution is never more than this (in fact notably less) if we vary the horizon used in the maximization problem that characterizes identification away from our base case. These are central estimates. Our estimated posterior distributions suggest values for this combined contribution of 11% and 74% respectively, for the $2.5th$ and $97.5th$ percentiles.

Despite finding a reduced role for risk news shocks in particular, we estimate that the risk news shock is contributing a lot to fluctuations in the central bank instrument, responsible for about 40% of the volatility of the policy rate, which the VAR impulse responses show fights vigorously and protractedly against its effects. We can conjecture therefore that, to the extent that unconventional monetary policy instruments are imperfect substitutes for interest rate policy, the recent protracted period at the zero bound could expose the economy to greater volatility from risk news shocks.

Finally, we try to fit a DSGE model to the VAR identified impulse responses to a risk news shock to see what they suggest about the kind of DSGE model that characterizes (at least this aspect of) the data. We use a DSGE model comprising the features of Smets and Wouters (2007) with Bernanke, Gertler, and Gilchrist (1999) financial frictions. We find that we can get this model to fit the shape of the impulse responses reasonably well, i.e. matching the conditional correlation of consumption, spreads, hours, investment, output generated by the risk news shock, but only if we allow that 75% of consumers are of ROT type. Without ROT consumers (holding other parameters constant at their MDE values) the model generates a rise in consumption in response to the risk news shock, which, from the point of view of the VAR, is counter-factual. A rise which is the corollary of a vigorous and protracted cut in the policy rate by the central bank to fight the fall in consumption that would otherwise ensue. Despite these successes, the estimation produces a value for the standard deviation of the risk news shocks 4 times that in the data, and even then the DSGE model struggles to track the dynamics of the risk proxy. These results are to some extent bound up with the weak financial accelerator mechanisms that the estimation computes, revealed by experiments where we strengthened the financial accelerator through calibration by increasing the cost of auditing on bankruptcy to values calibrated by BGG or

CMR. Despite doing this, we still get large values for the number of ROT consumers, for example 50% using the BGG calibration.

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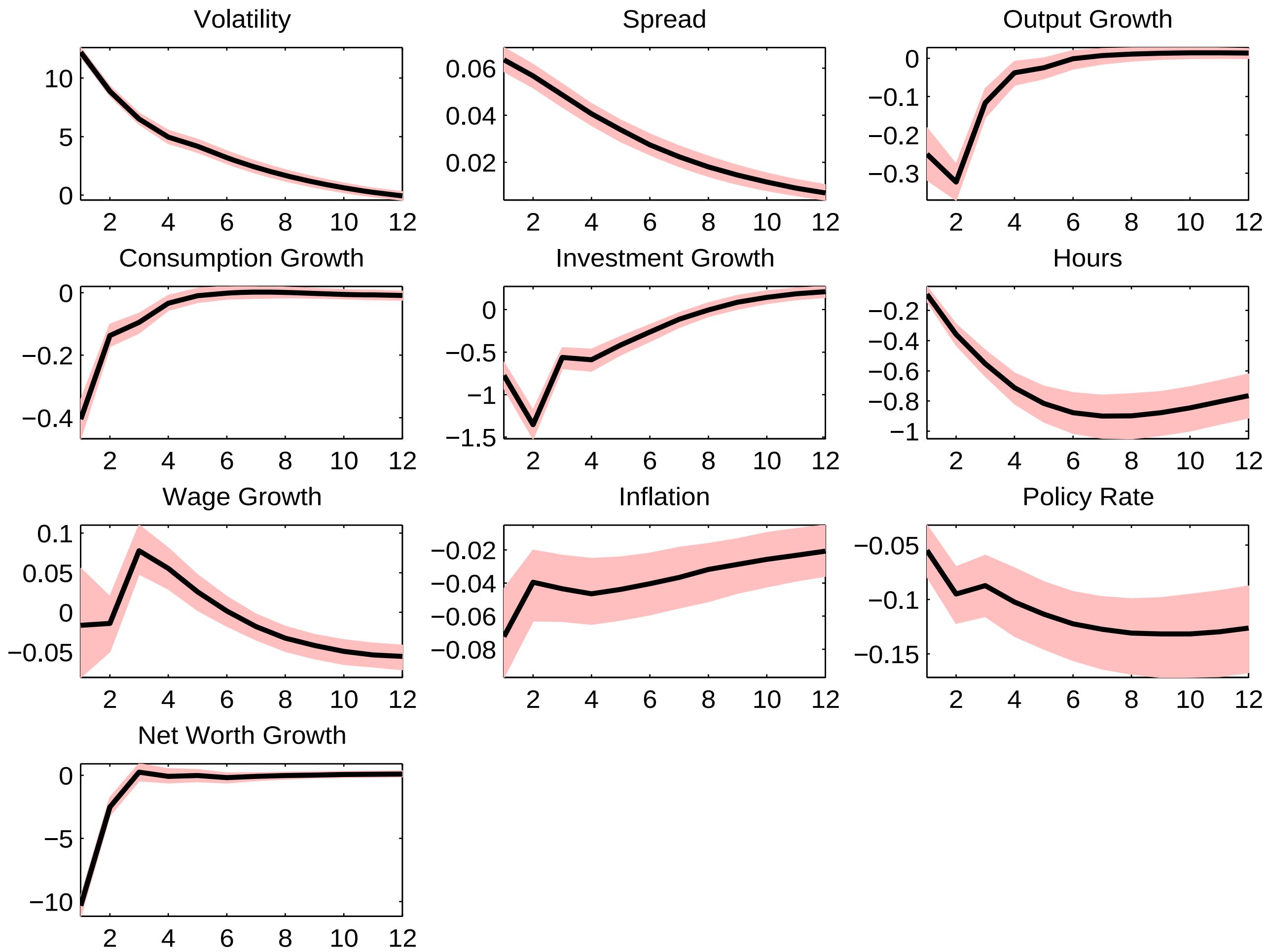
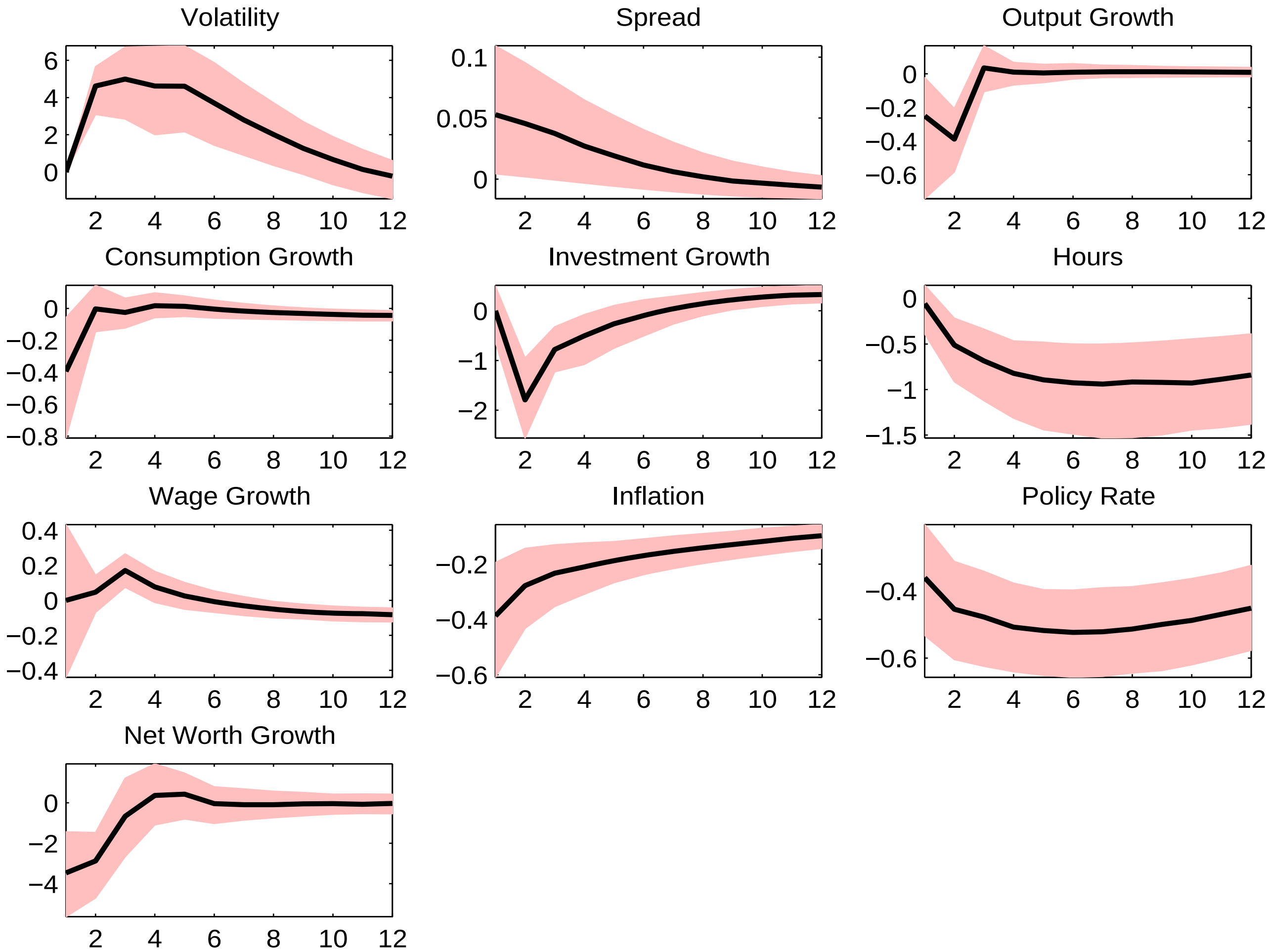
A Charts

Figure 1: Contemporaneous risk shock



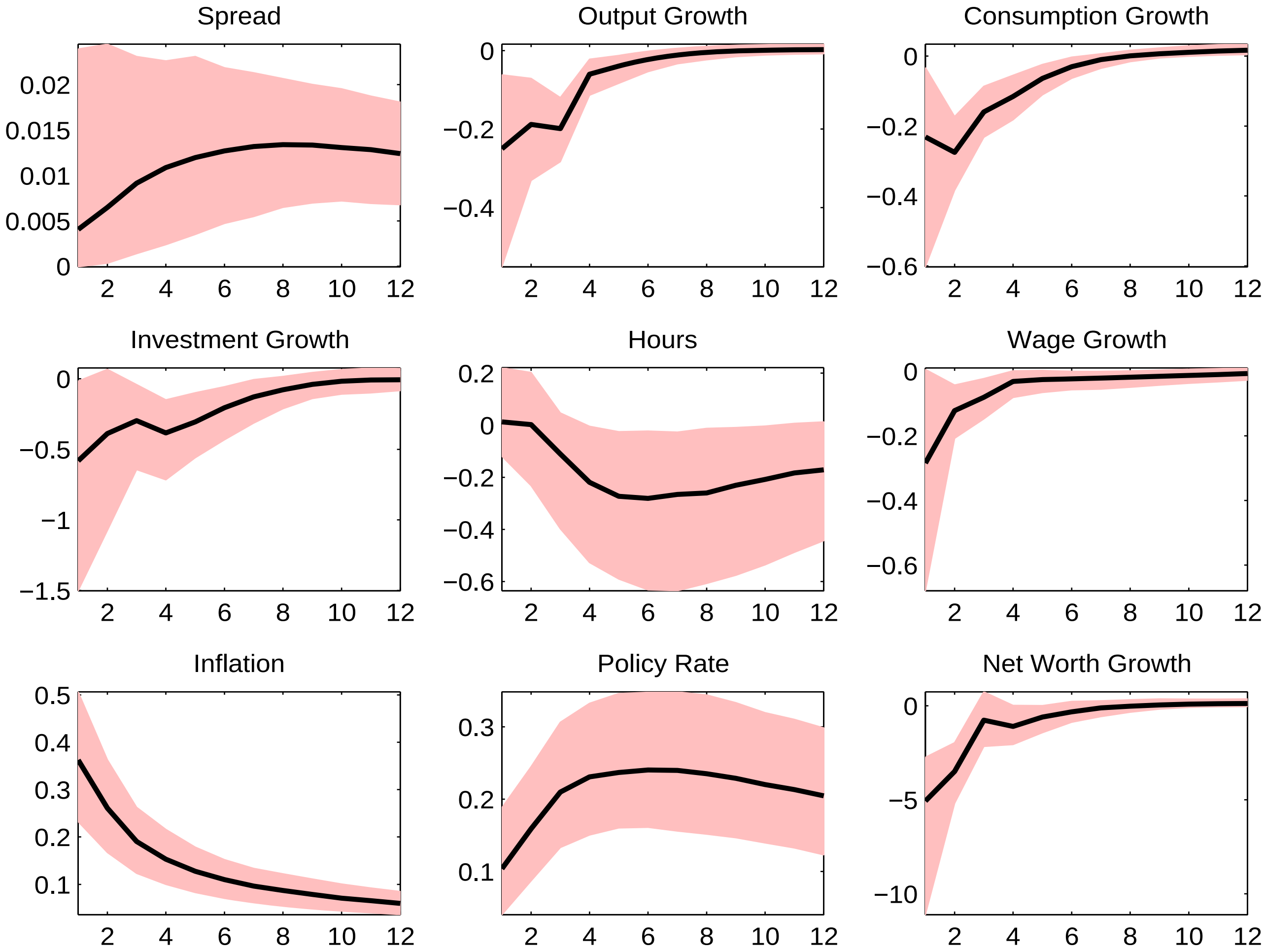
Notes: The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 32nd and 68th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage points.

Figure 2: Risk news shock



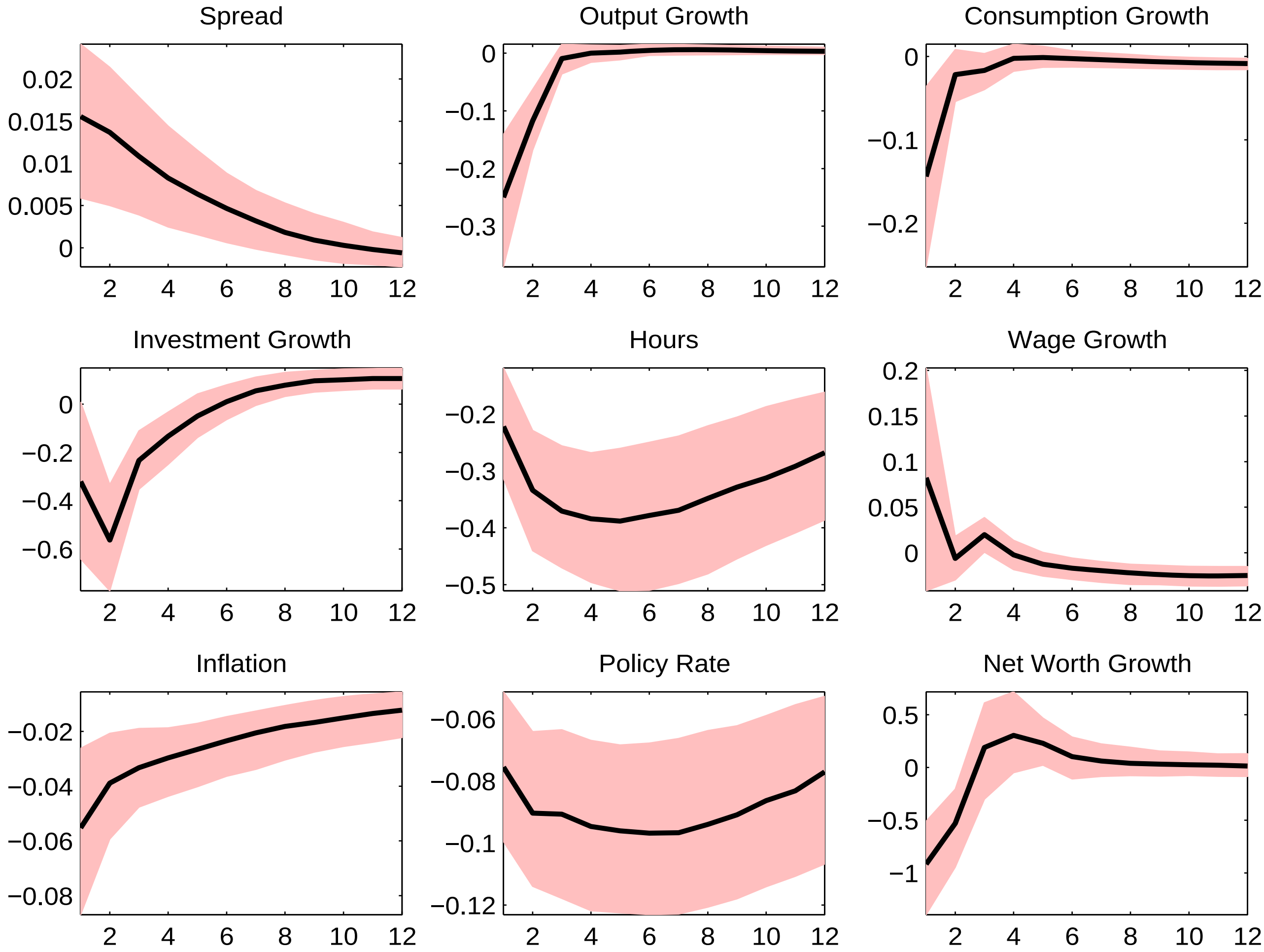
Notes: The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 32nd and 68th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage points.

Figure 3: Technology shock



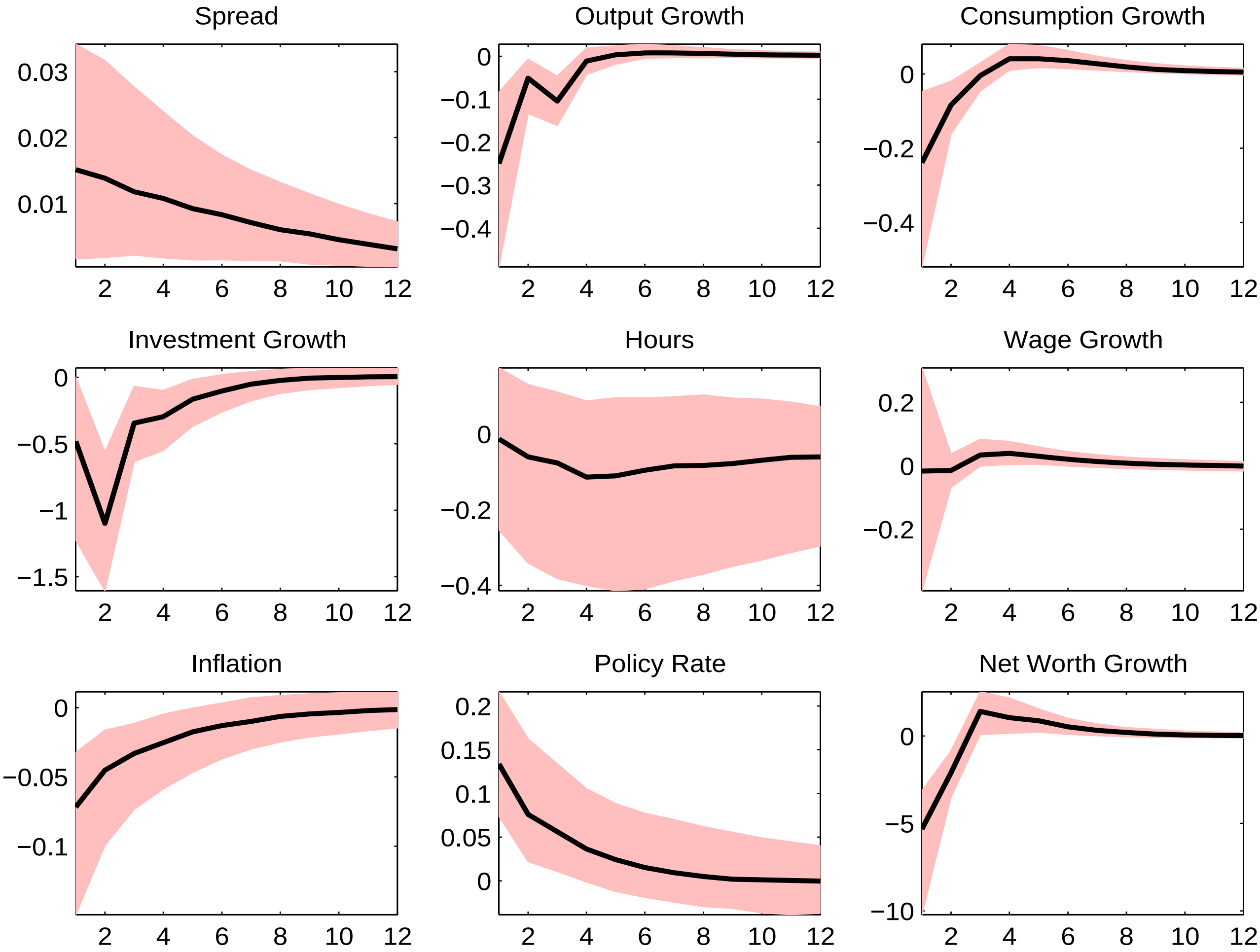
Notes: The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 32nd and 68th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage points.

Figure 4: Net worth shock



Notes: The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 32nd and 68th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage points.

Figure 5: Monetary policy shock



Notes: The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 32nd and 68th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage points.

Figure 6: Historical Decomposition Between 2007$Q1$ – 2010$Q2$

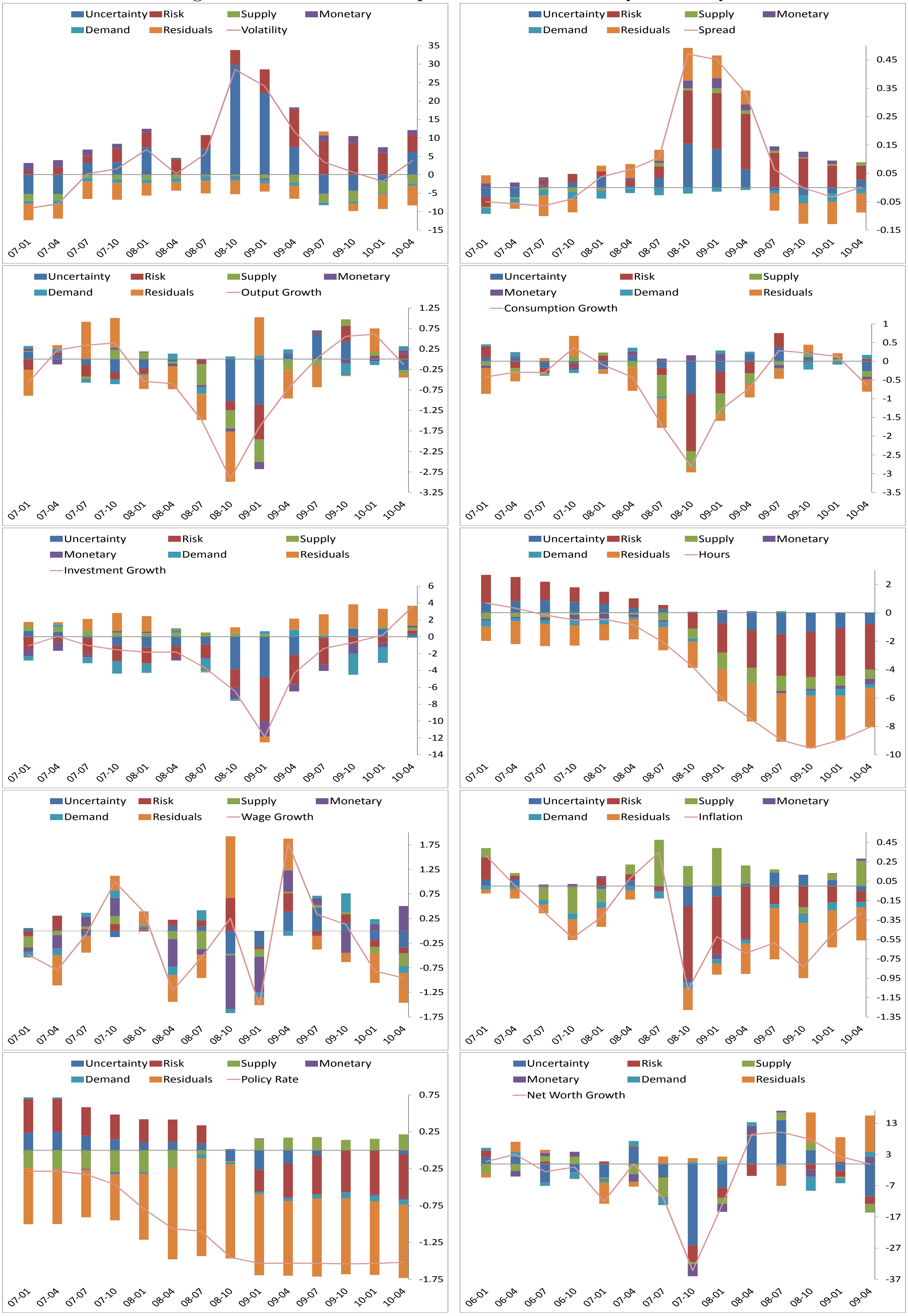
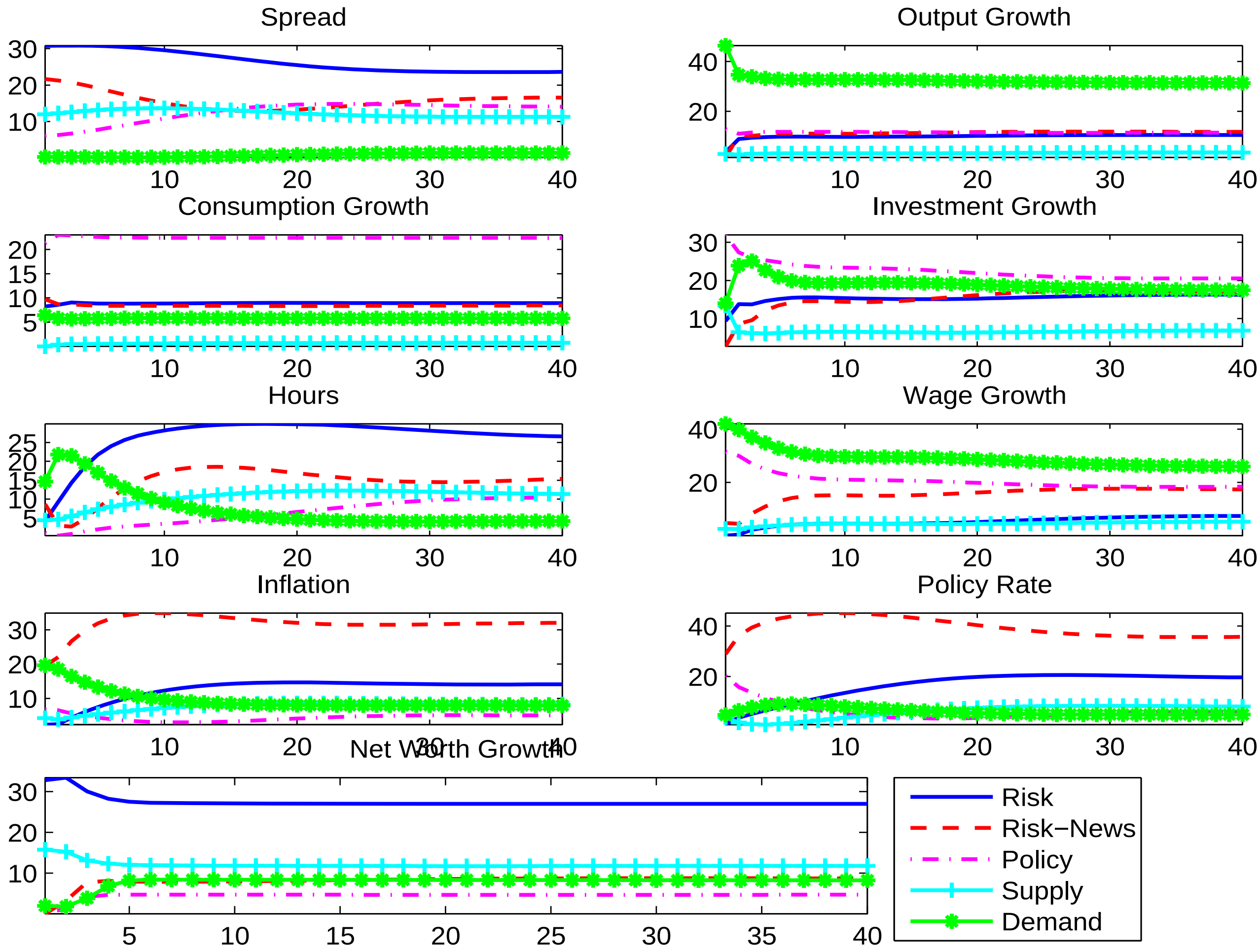
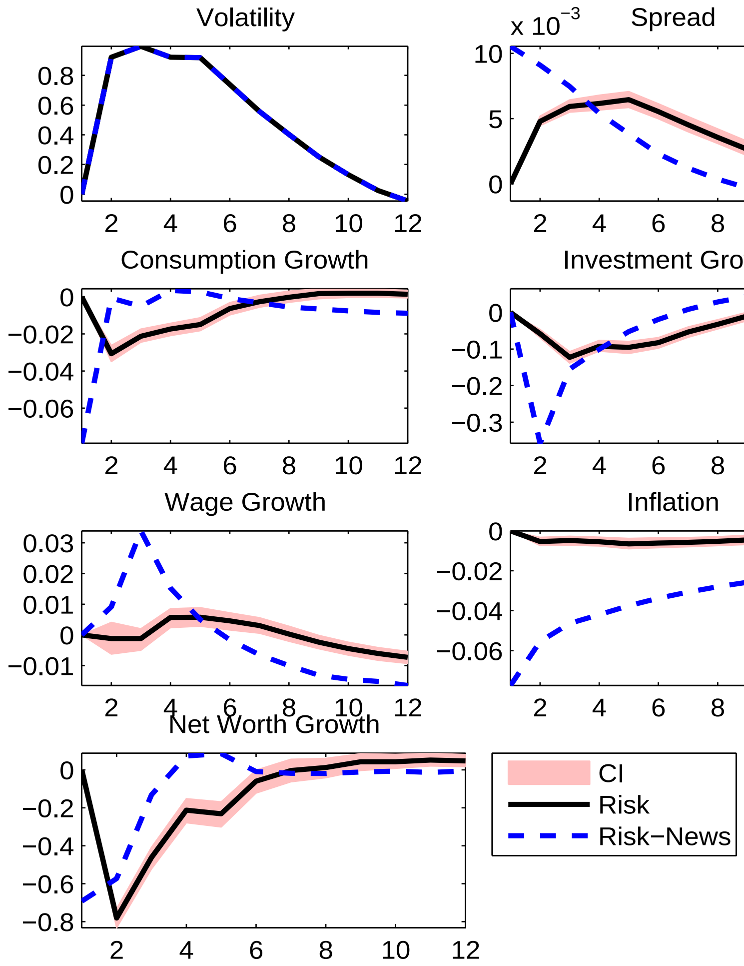


Figure 7: Forecast Variance Decomposition: VIX Measure



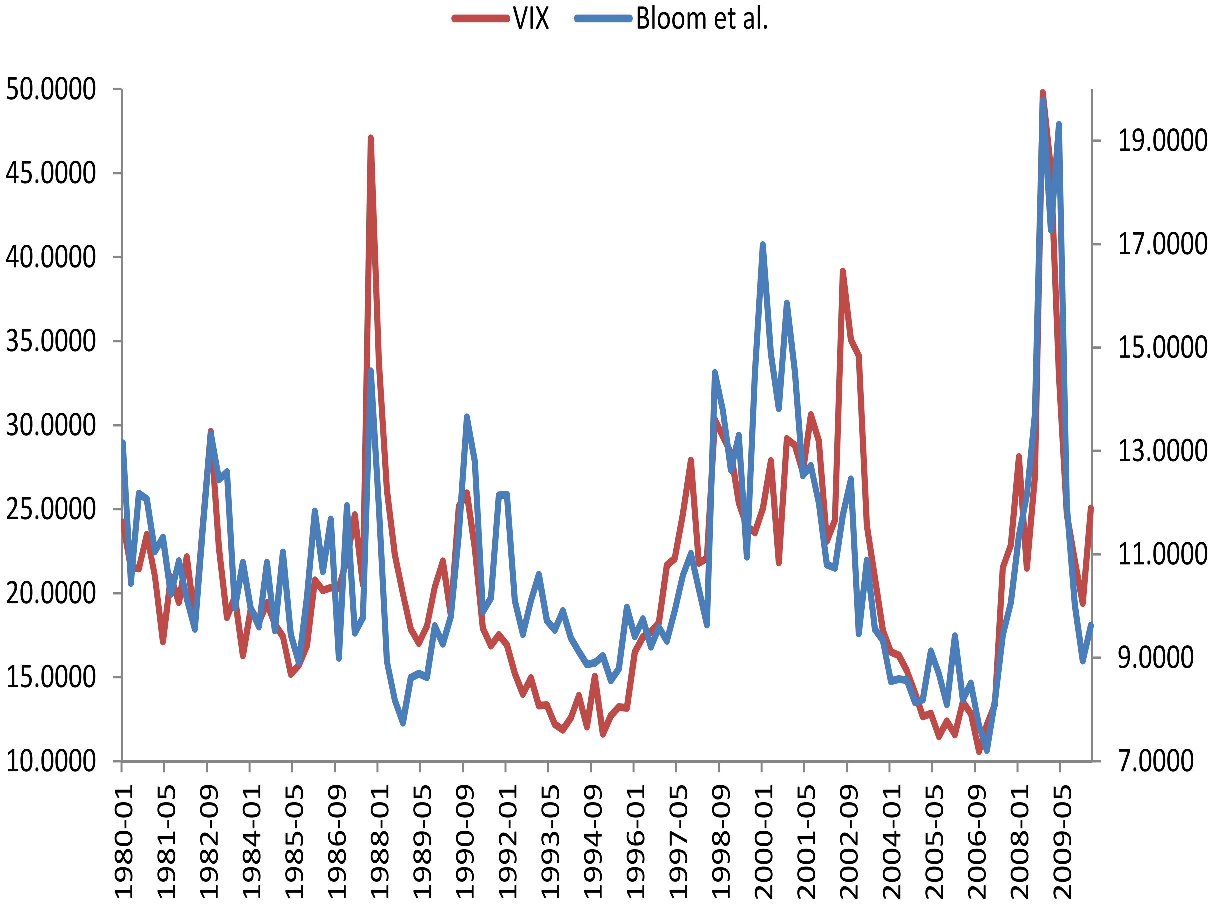
Notes: The horizontal axes represent the quarters at which the forecast error variance decomposition is calculated, the vertical axes are in percentages.

Figure 8: Risk versus Risk News Shock



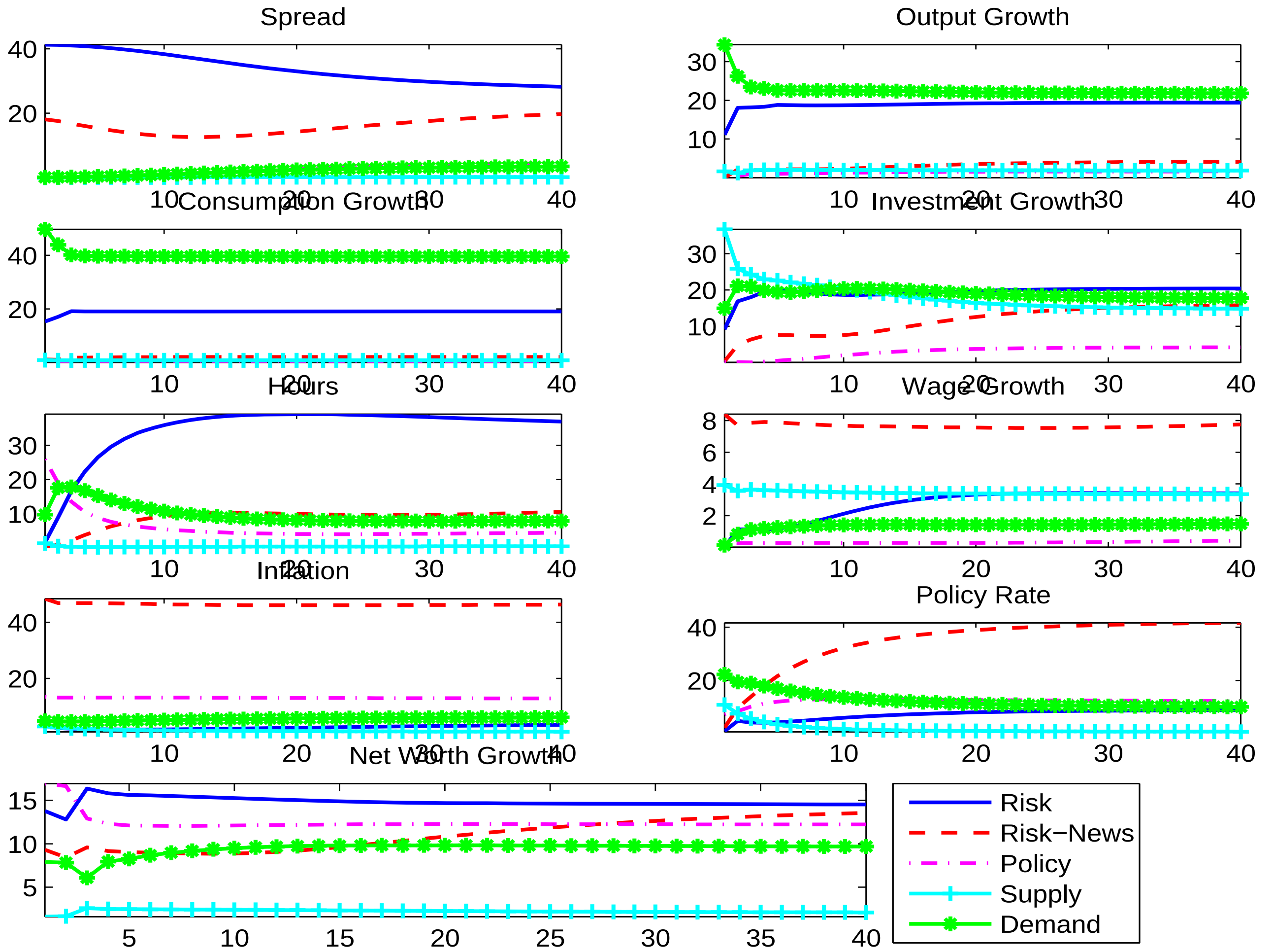
Notes: The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 32nd and 68th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage points.

Figure 9: VIX versus Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) Measure



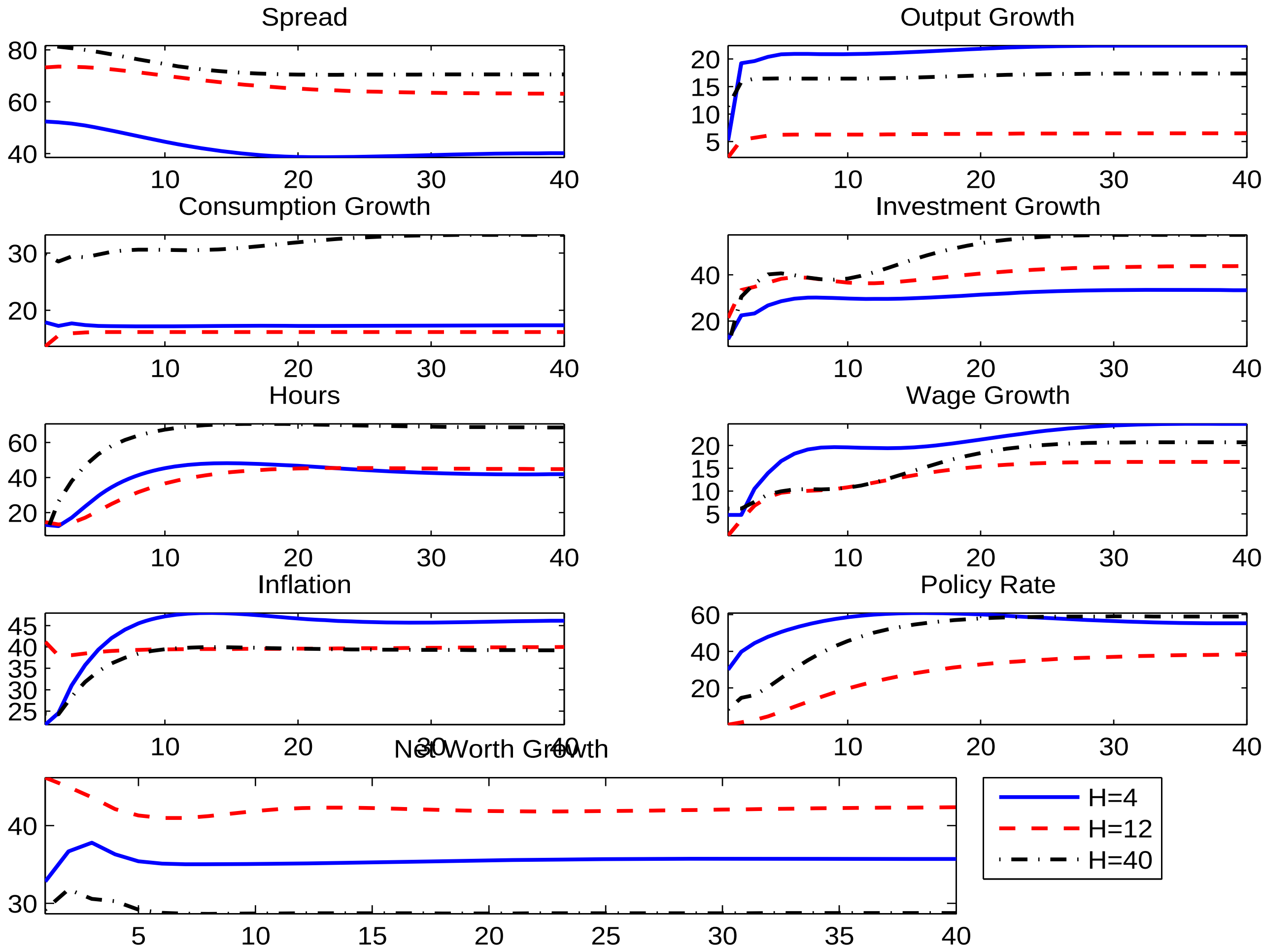
Notes: The Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) measure (right-hand side vertical axis) is the quarterly average of the interquartile range of firms' monthly stock returns for all public firms.

Figure 10: Forecast Variance Decomposition: Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) Measure



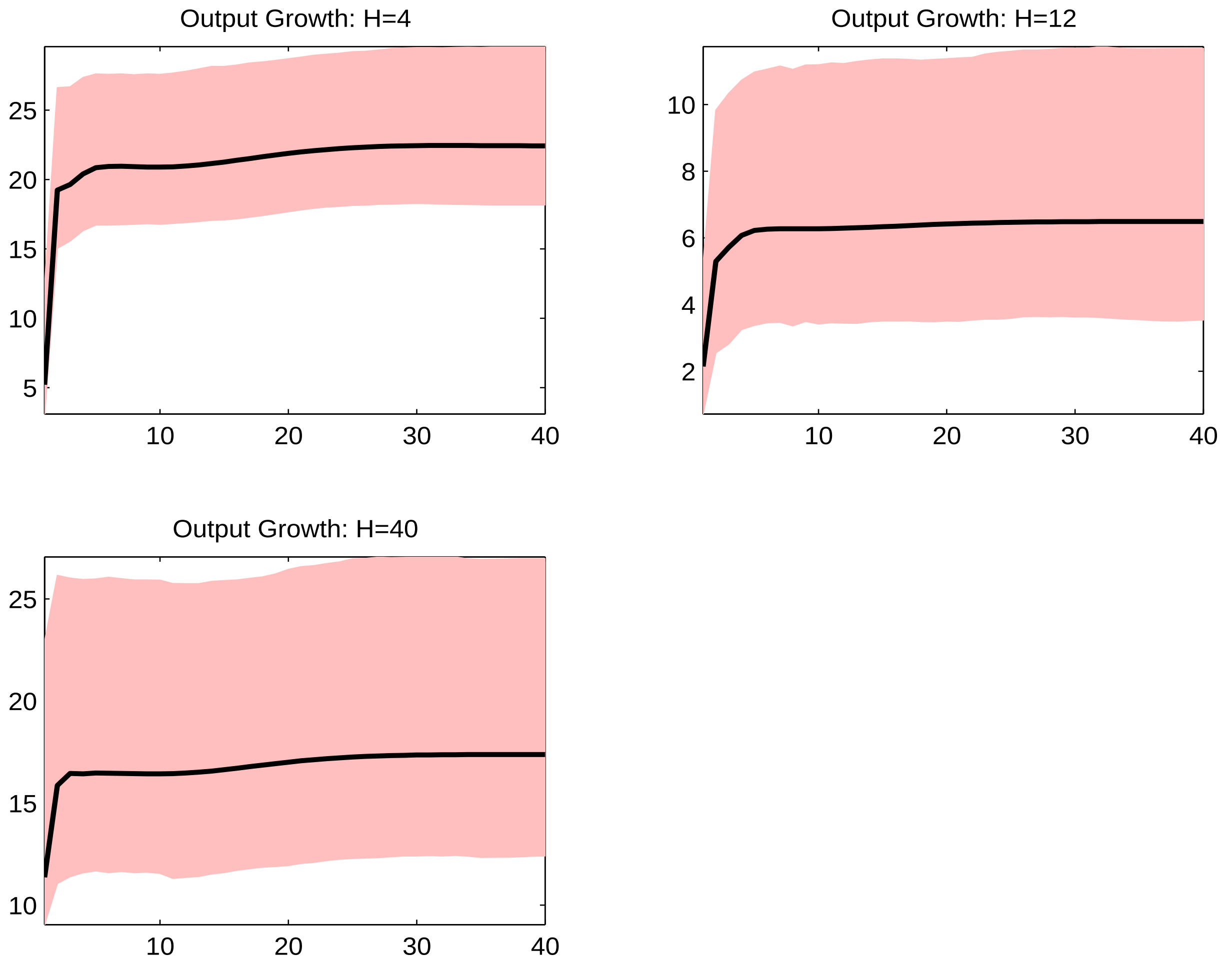
Notes: The horizontal axes represent the quarters at which the forecast error variance decomposition is calculated, the vertical axes are in percentages.

Figure 11: Forecast Variance Decomposition: H Sensitivity



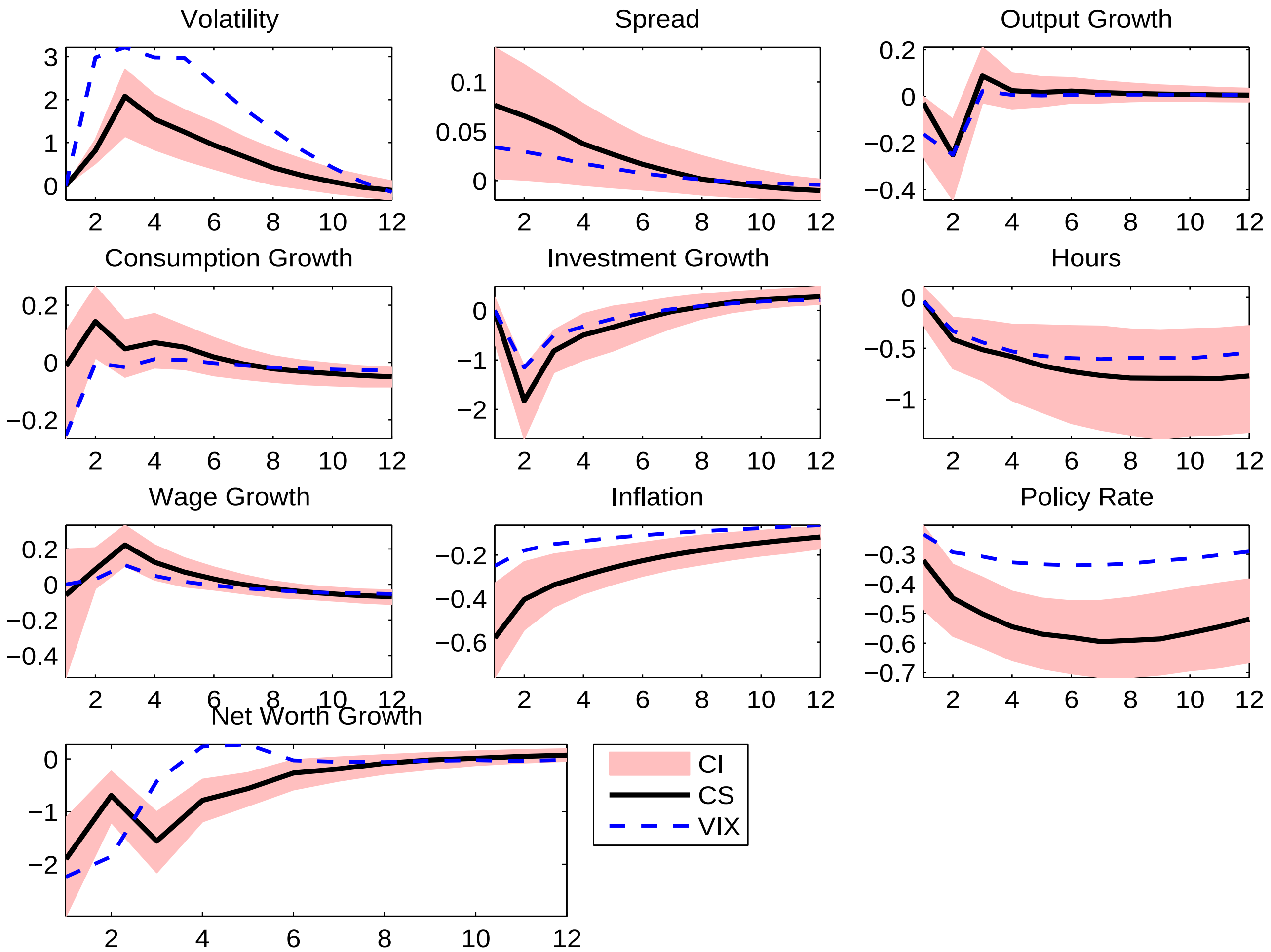
Notes: The horizontal axes represent the quarters at which the forecast error variance decomposition is calculated, the vertical axes are in percentages.

Figure 12: Uncertainty around Forecast Variance Decomposition Estimates



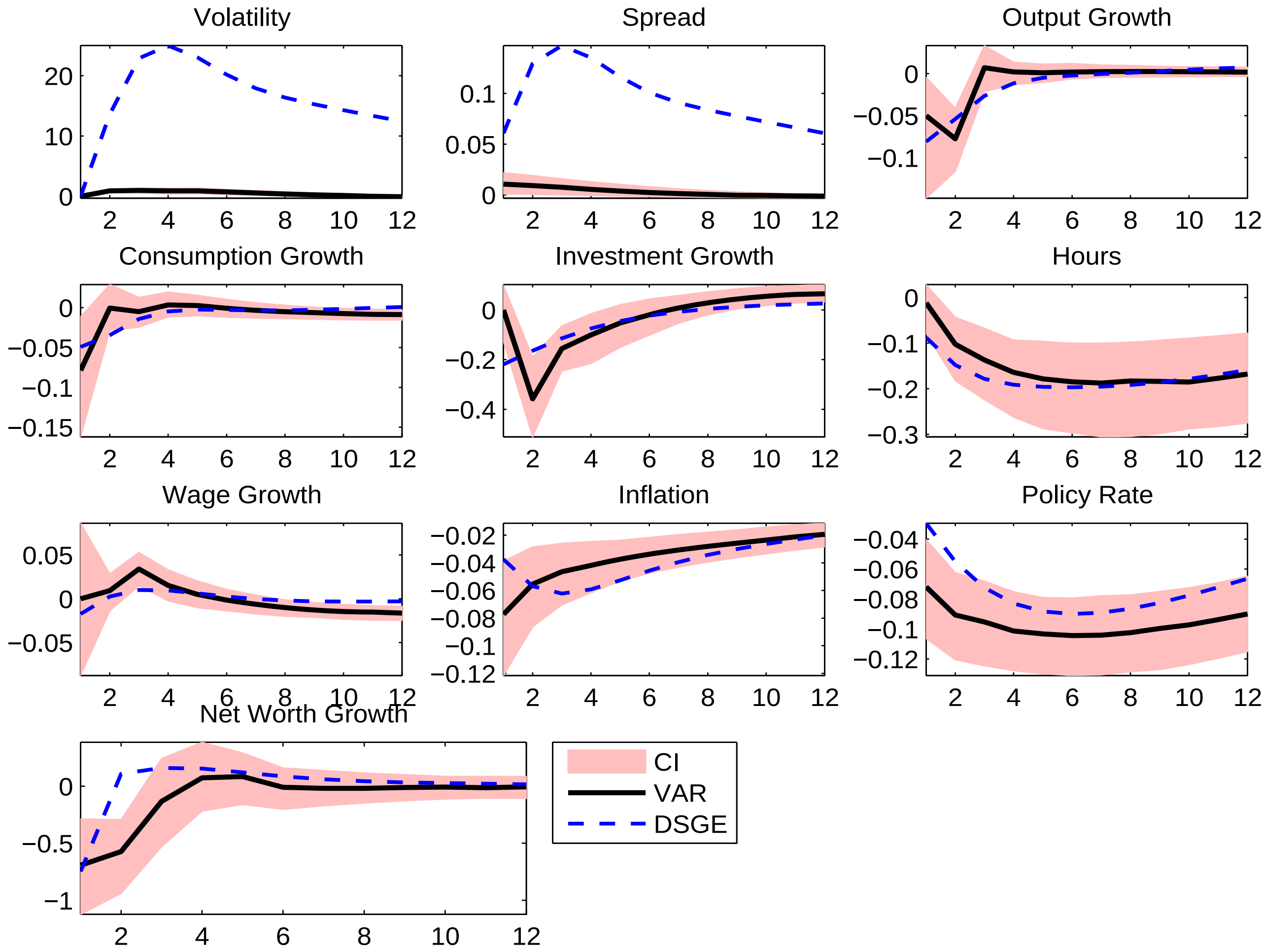
Notes: The solid line represents the estimate closest to the pointwise median impulse response function, and the shaded area is the corresponding 32nd and 68th percentiles of the posterior distribution. The horizontal axes represent the quarters at which the forecast error variance decomposition is calculated, the vertical axes are in percentages.

Figure 13: VIX versus Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) Measure: Risk News Responses



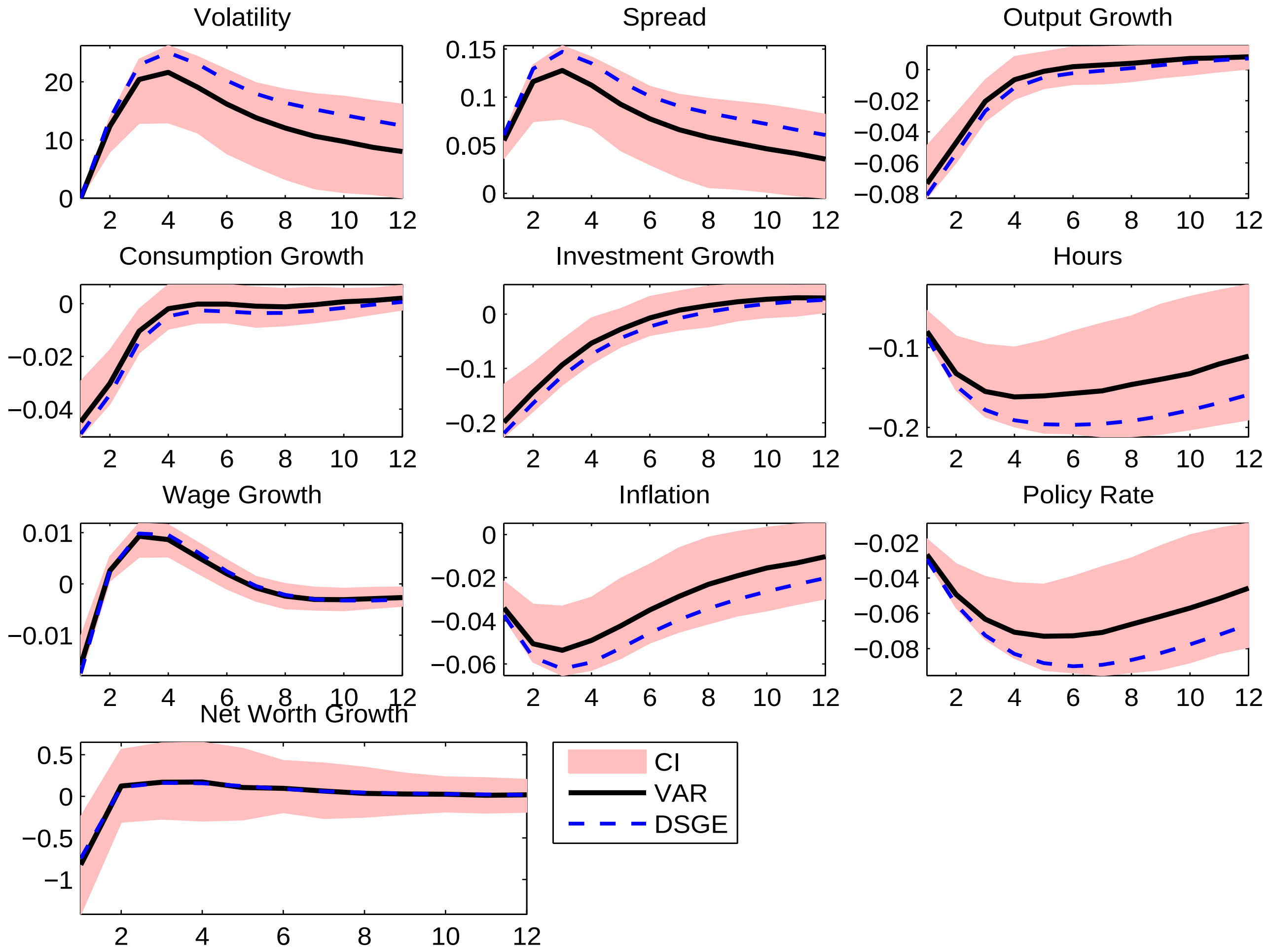
Notes: The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 32nd and 68th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage points.

Figure 14: DSGE Model Fit



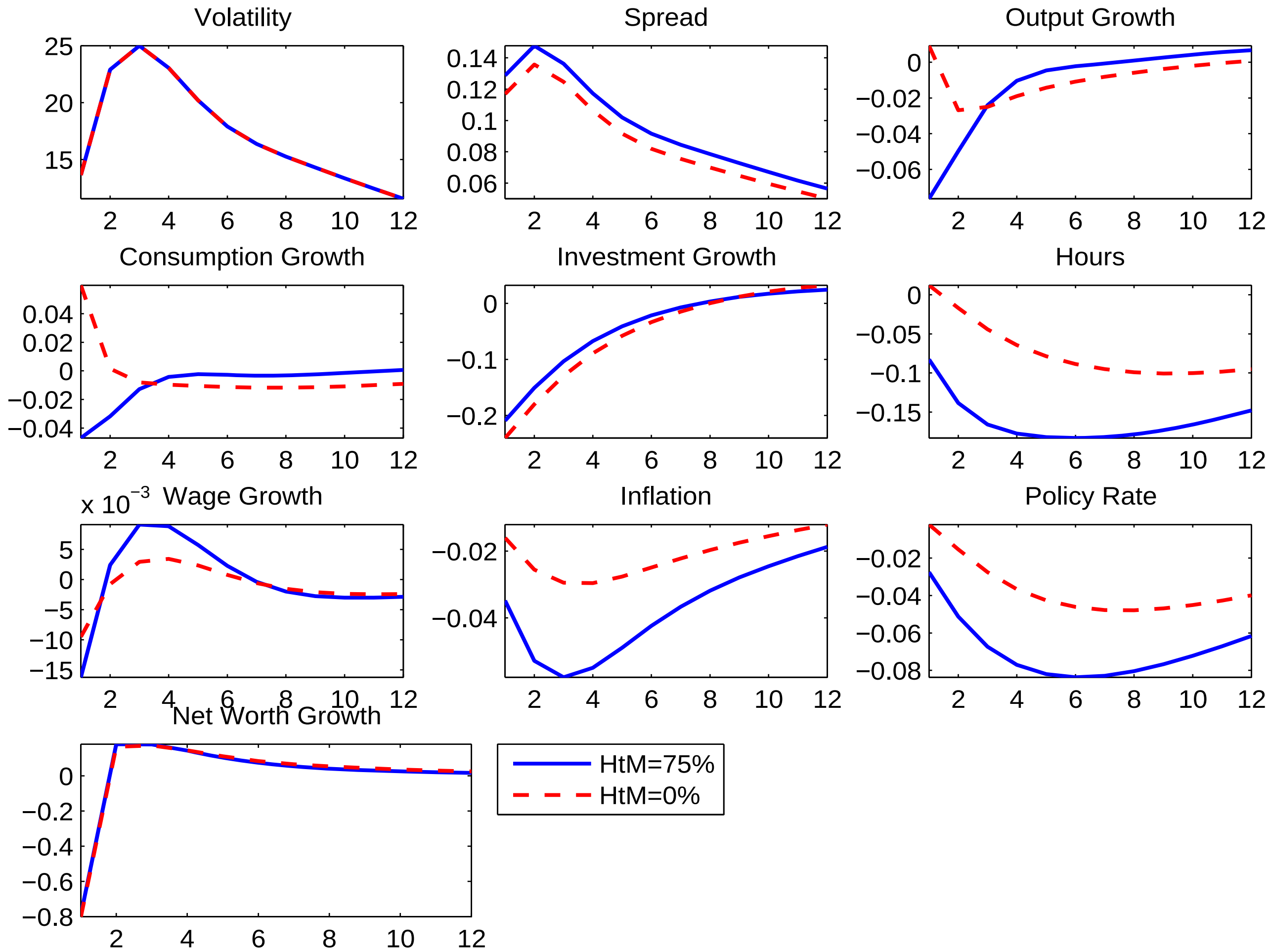
Notes: The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 32nd and 68th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage points.

Figure 15: Monte Carlo Simulations



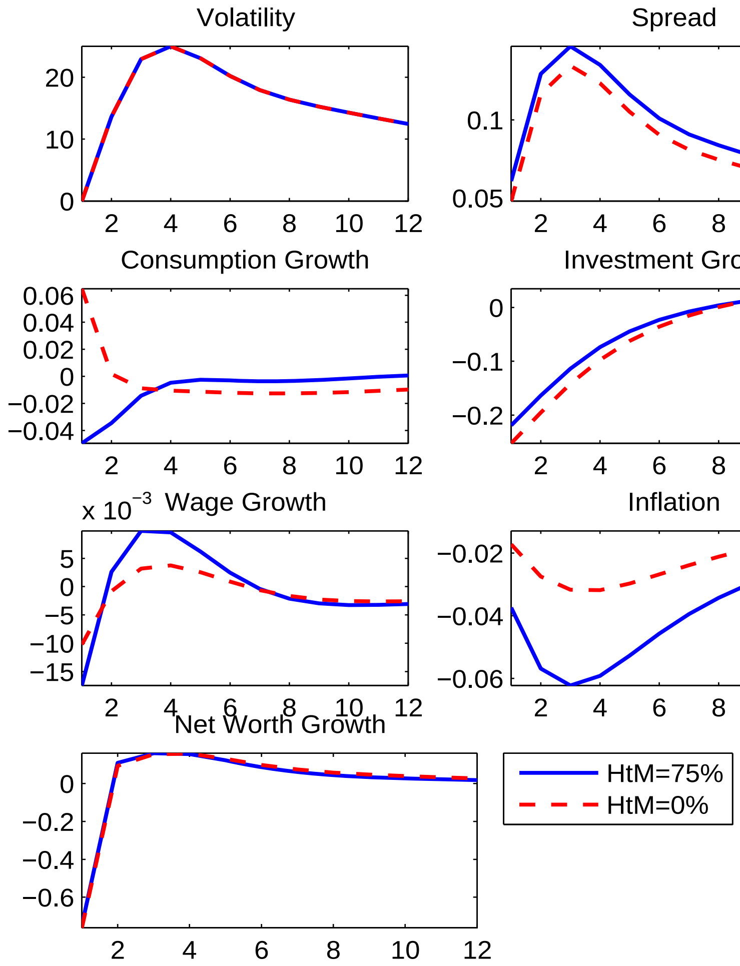
Notes: The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 32nd and 68th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage points.

Figure 16: HtM versus No HtM Consumers: Risk Shock



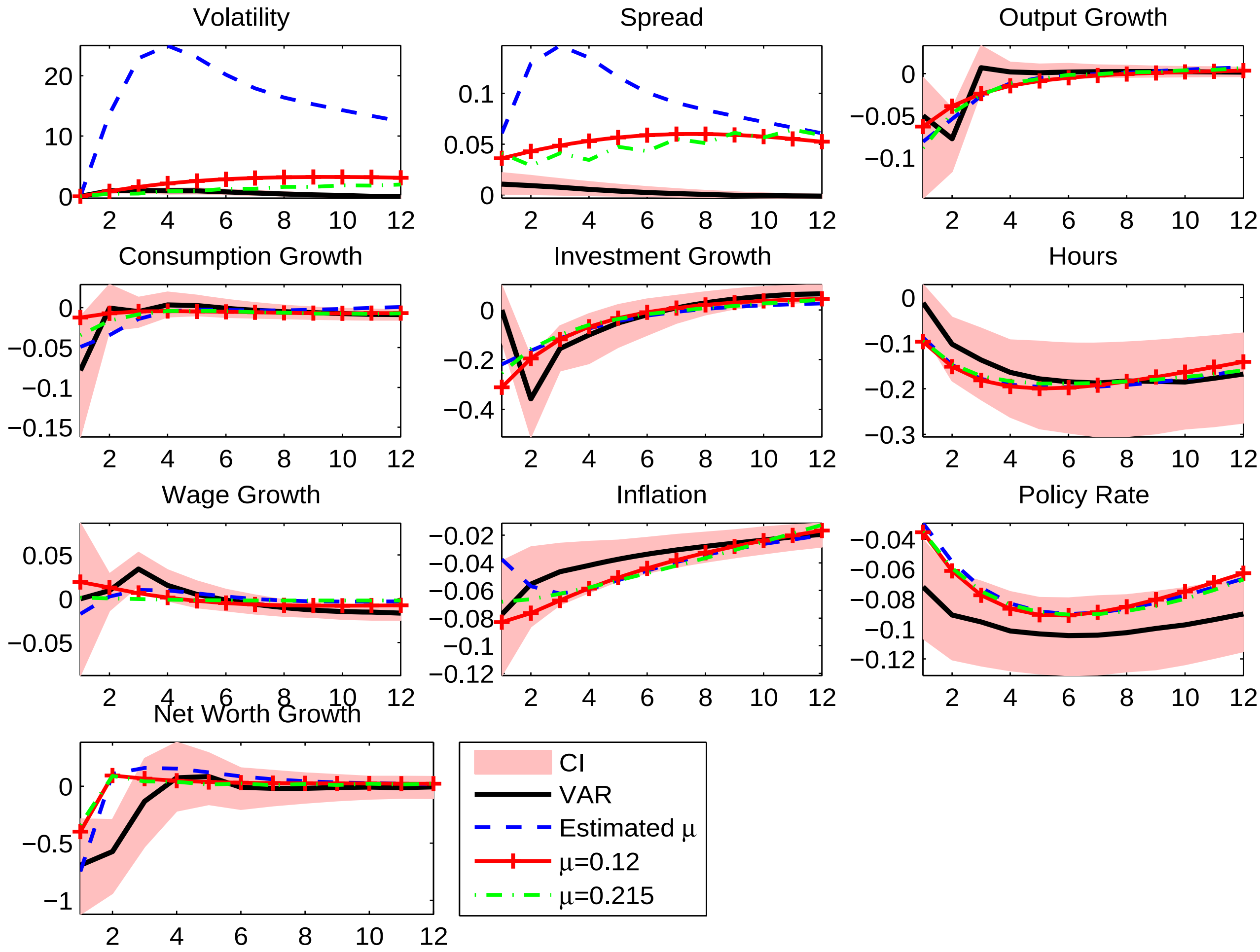
Notes: The horizontal axes are in quarters, the vertical axes are in percentage points.

Figure 17: HtM versus No HtM Consumers: Risk News Shock



Notes: The horizontal axes are in quarters, the vertical axes are in percentage points.

Figure 18: The relationship between the size of financial frictions and the magnitude of the shock



Notes: The horizontal axes are in quarters, the vertical axes are in percentage points.

B Tables

Table 2: Description of Parameters & Values

Symbols	Description	Calibrated Values	Status
	Structural Parameters		
γ	Steady State Growth Rate	1.004	Estimated
π	Steady State Inflation	1.018	Estimated
ϕ_p	Fixed Cost	1.003	Estimated
φ	Steady State Capital Adjustment Cost Elasticity	12.04	Estimated
α	Capital Production Share	0.278	Estimated
σ	Intertemporal Substitution	2.887	Estimated
λ	Habit Persistence	0.133	Estimated
ξ_w	Wages Calvo Parameter	0.905	Estimated
σ_l	Labour Supply Elasticity	9.949	Estimated
ξ_p	Prices Calvo Parameter	0.573	Estimated
i_w	Wage Indexation	0.011	Estimated
i_p	Price Indexation	0.716	Estimated
z	Capital Utilisation Adjustment Cost	0.407	Estimated
β	Time Preference Parameter	0.996	Estimated
ϵ_p	Goods Market Curvature of the Kimball Aggregator	10	Calibrated
ϵ_w	Labour Market Curvature of the Kimball Aggregator	10	Calibrated
τ	Capital Depreciation	0.025	Calibrated
λ_w	Steady State Labour Markup	1.500	Calibrated
$\frac{G}{Y}$	Steady State Government to GDP Ratio	0.180	Calibrated
	Financial Contract Parameters		
$\bar{\omega}$	Steady State Value of ω_t	0.118	Estimated
σ_ω	Steady State Standard Deviation of ω_t	0.727	Estimated
γ^e	Entrepreneur's Death Probability	0.965	Estimated
μ	Financial Friction Auditing Cost	0.050	Estimated
	Policy Parameters		
ϕ_π	Taylor Inflation Parameter	1.799	Calibrated
ϕ_r	Taylor Inertia Parameter	0.826	Calibrated
ϕ_y	Taylor Output Gap Parameter	0.089	Calibrated
ϕ_{dy}	Taylor Output Gap Change Parameter	0.224	Calibrated
ϕ_{RoT}	Share of RoT Consumers	0.750	Estimated
ϕ_d	Transfers Debt Coefficient	0.014	Estimated
ϕ_g	Transfers Government Spending Coefficient	0.117	Estimated
	Shock Parameters		
ρ_{1,σ_ω}	Risk Shock Persistence	1.608	Estimated
ρ_{2,σ_ω}	Risk Shock Persistence	-0.989	Estimated
ρ_{3,σ_ω}	Risk Shock Persistence	0.271	Estimated
$\sigma_\varkappa$	Risk News Shock Uncertainty	13.637	Estimated

[*] The values of the calibrated parameters are those used by Smets and Wouters (2007)