Risk news shocks and the business cycle*

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May 21, 2013

Abstract

We identify a 'risk news' shock in a VAR, modifying Barsky and Sims (2011)'s procedure by incorporating sign restrictions (and simultaneously identifying monetary policy, technology and demand shocks). The VAR implies that revelation about a future increase in risk causes an increase in spreads, and a fall in consumption, investment, hours, output, inflation and all this despite a vigorous and protracted cut in central bank rates. The 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%. Risk news shocks are observed to have substantially larger effects on the macroeconomy than contemporaneous risk shocks. We fit a DSGE model with financial frictions to these impulse responses and find that, in order to match the fall in consumption encoded in the VAR, we have to allow for 75% of consumers to be living hand-to-mouth.

JEL *Classification:* Cxx, Cxx, Cxx, Cxx

Keywords: xxx, xxx, xxx, xxx

*The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England. We would like to thank Nick Bloom, Christina Fuentes-Albero, Mark Gertler, Roland Wales, Wouter Den Hann, Matthias Paustian, Gunes Kamber and Christoph Thoenissen for very helpful comments on earlier versions of this work. Also participants at: CEF 2012 in Prague, EMF conference in Glasgow in 2013, a Bank of England research awayday, and the Loughborough conference on macro-pru, September 2012.

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1 Introduction

We use a modification of the method of Barsky and Sims (2011) (BS, hereafter) for identifying news shocks - which they applied to total factor productivity - to identify a risk news shock, an object studied recently by Christiano et al. (2013) (CMR). This shock captures fluctuations in the dispersion of returns to entrepreneurial activity in the private sector. *News* about this cross-sectional dispersion is revelation today about its future value. We compute the impulse responses of key macro and financial variables to this risk news shock in a ten variable VAR estimated for the US over 1980Q1-2010Q2. Following revelation that future uncertainty will increase, inflation, and real quantities (consumption, hours worked, investment) also fall, and this despite the fact that the central bank is estimated to respond to the risk news shock by cutting rates vigorously, and for a protracted period. Comparing like for like, risk news shocks have substantially larger effects on the macroeconomy than regular, unanticipated risk shocks (changes in risk today that were not previously revealed). Risk news shocks are shown to have depressed consumption and investment during the crisis, but the effect on output is more muted, suggesting perhaps that the response of (from the VAR's point of view) systematic fiscal stimulus was at work compensating.

We estimate that in the US, for the 1980Q1-2010Q2 period, risk news shocks contributed somewhere between 2% and 12% of the total volatility in output (depending on which of two risk proxies we use), roughly the same as that computed for technology shocks. The risk news and unanticipated risk shocks together contribute about 20% (regardless of which risk proxy we use). This combined contribution contrasts with a figure of 60% estimated for the combined contribution of these shocks using full information techniques in CMR.

Although risk news shocks on their own contribute little 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).

Finally, we take the DSGE model developed by Christiano et al. (2005) and Smets and Wouters (2007), modified to incorporate Bernanke et al. (1999) (BGG) financial frictions, and see whether this model can match the impulse responses to the risk news shock identified by the VAR. 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 consumers (following Gali et al. (2007) and Cogan et al. (2010)). In the absence of rule-of-thumb 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 estimated in the data, which is counter-factual, (at least in so far as the VAR impulse responses can be taken as a 'fact'). The modification to include rule-of-thumb consumers takes the model some way from the benchmark, however, since, at the optimum, our minimum distance estimator suggests that we need 75% of consumers to live hand-to-mouth. 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.

To locate what we have done in the large body of previous work: our paper can be seen as part of the literature that has sought to use optimizing models of dynamic macroeconomies to understand the causes of business cycles. This literature is taken to have begun with Kydland and Prescott (1982)'s emphasis on such cycles being adequately explained by technology shocks. Subsequent work has become too numerous and diverse to summarise compactly, and we mention here just a few significant milestones and controversies, including: Gali (1999)'s striking VAR evidence that identified technology shocks cause hours to fall, not rise, as in the RBC model; the effort to isolate monetary policy shocks and deduce what they implied about nominal rigidities (culminating in Christiano et al. (2005)) and quantifying their contribution to the business cycle; the conjecture that investment-specific technology shocks were important, (Greenwood et al. (2000), Justiniano et al. (2010)); and the bringing together of the implications of the sticky-price RBC Model on accounting for business cycles in Smets and Wouters (2007), which emphasized the importance of markup, discount rate and investment adjustment cost shocks, if the model was to be taken at face value.

Within this broad sweep of work, research that relates more closely to what we have done can be grouped into two, reflecting the two words 'risk news' in the title. Taking these words in reverse order, we begin with the effort to investigate the contribution of news shocks to business cycles. The framework of rational/model-consistent expectations leads naturally to the 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). 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. CMR's full information estimation focuses on revelations about future changes in the cross-section of returns to the entrepreneurs who borrow within a DSGE model with financial frictions (that could be summarised as CEE+BGG). An alternative way of identifying news shocks and quantifying their contribution was advanced by BS. They identify news shocks to total factor productivity (TFP) in a VAR. They begin with a TFP proxy derived from Solow residuals which they add to other variables of interest. A news shock is an object that is uncorrelated with today's TFP but contributes maximally to explaining the forecast errors variance of TFP at some finite horizon in the future. BS show that this scheme works in a monte carlo exercise where news shocks are recovered using this VAR method from data generated by a simple RBC model, modified to include news shocks. These experiments confirm (at least in the laboratory setting) that the in-principle invertibility problem noted by Blanchard et al. (2009) still leaves the econometrician, in practice, with adequate information to recover the news shocks well.

We study the same object articulated in CMR, but seek to identify it in a VAR. Building on the work of BS, we construct a risk news shock to be an object that is uncorrelated with a proxy for *risk* today but contributes maximally at some future horizon. We modify their method by confining the search for this maximum to the space of rotations of the reduced form VAR residual variance-covariance matrix that satisfy certain sign restrictions. This enable us to identify other shocks at the same time: shocks to monetary policy, technology and demand. With more than one shock identified, we can then quantify the contribution of risk news shocks to the business cycle relative to more familiar objects like technology and monetary policy shocks.

The second strand of research that precedes us relates to the 'risk' in 'risk news', and covers work on financial and risk or uncertainty shocks. Interest in financial shocks derives from a number of sources. One is simply the informal view that the recent crisis 'started' in the financial sector with defaults in the sub-prime mortgage market in the US. Even if one really thinks of this a proximate manifestation of other deeper forces, it may be constitute some kind of scientific progress to study models perturbed by exogenous financial drivers. A second motivation is that it has been commented for some time that the most popular models of financial frictions only mildly amplify conventional shocks like technology shocks. This is evident in the impulse responses plotted in Bernanke and Gertler (1989). But it is also true of Kiyotaki and Moore (1997) and the sticky price versions of related models built subsequently (for example, Iacoviello (2005)). This mild amplification has consequences that may be troubling: it implies financial factors cannot be predominant explanations for business cycles even during financial crises. And it has the consequence that optimal monetary and fiscal policy is little different whether the model has financial frictions or not.[1] However, financial shocks are often shown to have large effects and are a way to allow the financial friction models themselves to explain business cycles, a point made neatly 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. Justiniano et al. (2011) estimate a DSGE model with a Hall-like shock to the transformation of savings into capital. Fuentes-Albero (2012) considers a shock to the cost of bankruptcy in BGG, μ; Nolan and Thoenissen (2009) and Christiano et al. (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 (2010) examines shocks to the repayments of households who were lent to by financially constrained banks; Jermann and Quadrini (2012) study a model with shocks to the costs of changing the firm's debt/equity mix. Self-evidently, CMR's financial shock is distinctive: to recap, it is a shock to the cross-section of returns faced by the entrepreneurs who want to borrow. Their corresponding *news* shocks are revelations about future values of the dispersion of the cross section of returns.

What motivates considering such a shock? Formally, one could say that in CMR's full information exercise, the data, and the very large contribution to business cycles that they imply are made by the risk and risk news shocks, are sufficient motivation in themselves. Less formally, risk and risk news are intuitive features of the macroeconomy. CMR discuss the early failures of even eventually celebrated entrepreneurs like Steve Jobs and Bill Gates, emphasising that ex-ante (to their subsequent careers) one could view their futures as risky. As for risk news, there are many informal examples one could think of. One is the revelation of the phenomenon of global climate change. Prior to this, the distribution over future climate variables would have been relatively tight. Suppose some economic activities are more affected than others by climate change. Uncertain future climate change would therefore raise uncertainty over the returns to this cross section of activities differentially susceptible to climate change.

Note that the focus of this paper (as in CMR) is on fluctuations in the variance of *idiosyncratic* disturbances to productivity. This is to be distinguished from the interesting and complementary work on time series fluctuations in *aggregate* volatility.[2] 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

[1]For some examples, see: Vlieghe (2010), Crdia and Woodford (2009) and Fiore and Tristani (2012).

[2]Such fluctuations might also reasonably be described as 'risk shocks' but when we use this term we mean to refer only to changes in idiosyncratic volatility.

et al. (2011) and Born and Pfeifer (2011) (aggregate fiscal uncertainty), Mumtaz and Theodoridis (2012) (aggregate uncertainty in the open economy) and many others.

2 Our strategy for identifying the risk news shock

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 'maximisation' step following BS.

2.1 The Empirical Model

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

The starting point of our empirical analysis is a vector autoregressive model of order K – VAR(K)

$$y_t = \sum_{i=1}^{K} \Theta_i y_{t-i} + u_t \tag{2.1}$$

where u_t is the $N \times 1$ vector of reduced-form errors that is 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 et al., 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

$$\theta|\Sigma \sim N(\theta_0, \Sigma \otimes \Omega_0),\ \Sigma \sim IW(v_0, S_0). \tag{2.2}$$

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 it is explained by Bandbura et al. (2010) they can be constructed using the following dummy observations

$$Y_D = \begin{pmatrix} \frac{diag(\delta_1\sigma_1...\delta_N\sigma_N)}{\lambda} \\ 0_{N\times(K-1)N} \\ .... \\ diag\,(\sigma_1...\sigma_N) \\ .... \\ 0_{1\times N} \end{pmatrix} \text{ and } X_D = \begin{pmatrix} \frac{J_K \otimes diag(\sigma_1...\sigma_N)}{\lambda} \\ 0_{N\times NK} \\ .... \\ 0_{1\times NK} \end{pmatrix} \tag{2.3}$$

where $J_K = diag\,(1, 2, ..., K)$ and $diag$ denotes the diagonal matrix. The prior moments of (2.2) are just functions of Y_D and X_D, $\Theta_0 = Y_D X'_D \left(X_D X'_D\right)^{-1}$, $\Omega_0 = \left(X_D X'_D\right)^{-1}$, $S_0 = (Y_D - \Theta_0 X_D)\,(Y_D - \Theta_0 X_D)'$ and $v_0 = T_D - NK$. Finally, the hyper-parameter λ controls the tightness of the prior.

Since the normal-inverted Wishart prior is conjugate, the conditional posterior distribution of this model is also normal-inverted Wishart (Kadiyala and Karlsson, 1997)

$$\theta|\Sigma, Y \sim N(\bar{\theta}, \Sigma \otimes \bar{\Omega}), \;\; \Sigma|Y \sim IW(\bar{v}, \bar{S}), \tag{2.4}$$

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 $\bar{S} = \hat{\Theta}XX'\hat{\Theta}' + \Theta_0\Omega_0^{-1}\Theta_0 + S_0 + \hat{U}\hat{U}' - \bar{\Theta}\bar{\Omega}^{-1}\bar{\Theta}'$.

The values of the persistence – δ_i – and the error standard deviation – σ_i – parameters of the AR(1) model are obtained from its OLS estimation. Sensitivity analysis reveals that the results are robust to different selections of VAR lags.

2.2 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)

$$y_t = B\,(L)\,u_t \tag{2.5}$$

Under the assumption that a mapping between the reduced-form errors and the structural shocks exists

$$u_t = A\varepsilon_t \tag{2.6}$$

such as $AA' = \Sigma$, the h step ahead forecast error can be expressed as

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

where $\tilde{A}$ is the lower triangular matrix obtained from the Cholesky decomposition of Σ and Q is an orthonormal matrix such as $Q\,(\omega)\,Q\,(\omega)' = I_{dy}$, where I_{dy} is the $dy \times dy$ identity matrix and $\omega \in \left[\begin{array}{cc} 0 & 2\pi \end{array}\right]$ denotes the rotation angles.

The share of the forecast error variance of variable i attributable to the structural shock j at horizon

h is written as:

$$\Omega_{i,j}(h) = \frac{e_i'\left(\sum_{\tau=0}^{h} B_\tau \widetilde{A} Q(\omega) e_j e_j' Q(\omega)' \widetilde{A}' B_\tau\right) e_i}{e_i'\left(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau\right) e_i} \tag{2.7}$$

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 the uncertainty process is exogenous and driven by two random disturbances the unanticipated shock – $\varepsilon_{\sigma_\omega,t}$ – and the anticipated one – $\eta_{news,t-1}$.

$$\ln \sigma_{\omega,t} = (1-\rho_\sigma)\,\sigma_\omega + \rho_\sigma \ln \sigma_{\omega,t-1} + \varepsilon_{\sigma_\omega,t} + \varepsilon_{t-1}^{news} \tag{2.8}$$

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

$$\Omega_{1,1}(h) + \Omega_{1,2}(h) = 1 \tag{2.9}$$

However, it is unlikely that condition (2.9) holds at all horizons in a multivariate VAR model. Hence, as suggested by BS, we select the second column of the impact matrix – $\widetilde{A}Q(\omega)$ – that comes as close as possible to making equation (2.9) hold over a finite set of horizons.

Since we intend to identify additional more 'standard' macroeconomic – technology, demand, monetary policy – shocks as well as we want the responses of some variables to a risk news shock to satisfy certain 'qualitatively' restrictions, we combine the BS with the 'sing restriction' methodology following Uhlig (2005) and Canova and De Nicolo (2002).

To be precise, we find the vector ω that maximizes the forecast error variance associated with the second 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

$$\omega^* = \arg\max \sum_{h=0}^{H} \Omega_{i,j}(h) = \arg\max \sum_{h=0}^{H} \frac{e_i'\left(\sum_{\tau=0}^{h} B_\tau \widetilde{A} Q(\omega) e_j e_j' Q(\omega)' \widetilde{A}' B_\tau\right) e_i}{e_i'\left(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau\right) e_i} \tag{2.10}$$

subject to

$$A(1,j) = 0 \tag{2.11}$$

where $j > 1$.

$$A_{2.2} = F(sign) \tag{2.12}$$

where $A_{2.2}$ is a 9×9 submatrix of $A = \begin{bmatrix} A_{1.1} & A_{1.2} \\ A_{2.1} & A_{2.2} \end{bmatrix}$

$$Q(\omega)\,Q(\omega)' = I \tag{2.13}$$

where I is the 10×10 identity matrix. Constraint (2.11) implies that no other shock expect the unanticipated uncertainty shock has a contemporaneous effect on uncertainty. Constraint (2.12) ensures that ω^* satisfies the sign restrictions associated the structural shocks. By ordering the uncertainty variable first, we get the from the Choleski factorisation of Σ

$$\widetilde{A} = \begin{bmatrix} \sigma_\sigma & 0 \\ \widetilde{A}_{2,1} & \widetilde{A}_{2,2} \end{bmatrix} \tag{2.14}$$

Next we select ω^* so the rotation matrix $Q_{2,2}(\omega^*)$ satisfies the sign restrictions for $A_{2,2}$. Defining now $Q(\omega^*)$ as follows

$$Q(\omega^*) = \begin{bmatrix} 1 & 0 \\ 0 & Q_{2,2}(\omega^*) \end{bmatrix} \tag{2.15}$$

it is not hard to see that $Q(\omega^*)$ satisfies both (2.12) and (2.13).

Table 1 summarises 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								
Wages-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 entail a change in the degree of impatience, or a fiscal impulse) raises output, inflation and interest rates. Finally, a contractionary monetary policy shock raises interest rates on impact, lowering output and inflation. The same restrictions are also imposed in $t+1$.

2.3 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): log difference of real GDP, real consumption, real gross investment and real wage, log hours worked, the log difference of the GDP deflator 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[3] (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.[4] As an alternative, we use a measure of the interquartile range of the cross section of stock returns in the US, downloadable from Bloom's website.

[3] As in CMR

[4] VIX is a popular measure of the implied volatility of S&P 500 index options

2.4 VAR Results

Chart 2 presents how the macroeconomic aggregates considered in this study respond to risk news shock where our chosen value for h, the horizon at which the risk news shock is constructed to explain the maximum proportion of forecast error variance in the risk proxy, is 4 quarters. 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 - results (e.g. the impulse responses to the identified shocks) are little changed for models with 1,2 and 4 lags. The black lines and shaded areas require some explanation which 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 VARs residual variance-covariance matrix that satisfy our sign and zero restrictions. iii) we search across them to find the rotation that maximises the forecast error variance criterion, giving us 1000 '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. (By 'pointwise' we mean that at each horizon t 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 t; analogously for other percentiles). (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.)

Our volatility proxy (in this benchmark case, the VIX), peaks somewhat *after* the first period, at which point the shock has hit, meaning that there has been some revelation about a future change in risk, and it remains above its steady state for almost 3 years.[5] A shock large enough to cause the VIX risk proxy to rise by almost 4.5% (compared to the 86% 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 $-2pp$) and to a relative temporary drop in consumption (-0.4%). As consequence GDP contracts ($-0.25pp$ by construction) and weak demand is translated to low hours (which fall by 1%) and inflation (which falls by 0.4pp). Consistent with the rise in spreads and lower investment, net worth drops by $4pp$. These falls are despite the monetary authority cutting rates aggressively and for a protracted period. Note that the response we are looking at is to a shock that drove the VIX risk proxy up by about a quarter of the increase seen in the financial crisis. Relatedly, the shock we study here is one that drives spreads up by only 5 basis points, compared to the very large fluctuations in spreads seen in the crisis.

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 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.[6]

[5] 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.

[6] 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.

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 (in so far as the VAR can tell - all are somewhat ill-determined) in response to these shocks.

The first headline of our analysis can be seen in Chart 7 which shows the forecast error variance decomposition (for the 9 'endogenous' series, i.e. excluding 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 have larger effects.

Chart 6 provides the historical decomposition of the VAR series over the recent past, 2006Q1-2010Q2. Since there are actually many VARs reported earlier, the construction of the chart requires some explanation, namely, which historical decomposition have we chosen? Recapping on text above, we have 1000 posterior draws for the VAR parameters, and each one generates a maximum corresponding to the output of the Barsky-Sims part of the procedure. For each of these 1000 VARs, we can report a historical decomposition 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 contributions of the shocks that have not been identified 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. 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. Our method has some advantages and disadvantages. An advantage is that the identification is not pinned to any one model of financial frictions, so in that sense is robust. However, we are forced to treat the time series of 'risk' as an observable, so our method is only robust to the model misspecification we hope to avoid in so far as this is a good proxy. By committing to a particular model of financial frictions, CMR are able exclude risk proxies from their observeables, (though to the extent that the risk proxy is used ex post to corroborate the model-recovered process for risk, their method also relies on the accuracy of that risk proxy). It is incumbent on us to show that this result does not depend entirely on the VIX as our risk proxy.

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, 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, but, in the absence of measurement error, and if the distribution of returns were normal, will equal the standard deviation. Chart x plots this new risk proxy, which we compute have a correlation coefficient of 0.75 with the VIX.

Chart 10 compares the impulse responses in the VAR with the cross section of returns measure (black line, plus cloud, computed as above labelled 'CS' and 'CI', respectively) to the VAR estimated with the VIX (red line, labelled 'VIX', where this red line is the median (computed the same way as above) and so directly comparable to the black line). We see that the risk news shock in the cross section returns VAR induces very similar impulses to our observeables, with the exception that the risk proxy itself rises a lot more in the future.

Chart 9 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, less than 5%. 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 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 differently.

3 DSGE Model with financial frictions

We move on now to see whether a suitably specified DSGE model can fit the impulse responses to the risk news shock estimated in the VAR.

The next subsection briefly discusses the linearised 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 patient consumers who supply labour to differentiated and sticky wage labour unions. There are impatient 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 and a central bank. 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 the private sector, in our case between banks and entrepreneurs who construct capital goods for use by the intermediate goods producers, a friction which results in 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 et al. (2007) and Cogan et al. (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 hand-to-mouth (or rule–of-thumb) households simply consume all their labour income (and a transfer that equates the steady-state consumption between non-optimising and optimising 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 live hand-to-mouth in this way.

3.1 Linearised 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 utilisation (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

$$\begin{aligned} y_t &= c_y c_t + i_y i_t + z_y z_t + \varepsilon_t^g \\ &+ \frac{\mu}{\bar{\pi}\gamma} G(\bar{\omega}, \sigma_\omega) \bar{R}^k \frac{\bar{K}}{\bar{Y}} \left(R_t^k + q_{t-1} + k_{t-1} + \frac{\frac{\partial G(\bar{\omega}, \sigma_\omega)}{\partial \omega}}{G(\bar{\omega}, \sigma_\omega)} \bar{\omega}\omega_t + \frac{\frac{\partial G(\bar{\omega}, \sigma_\omega)}{\partial \sigma_\omega}}{G(\bar{\omega}, \sigma_\omega)} \sigma_\omega \sigma_{\omega,t} \right) \end{aligned} \tag{3.1}$$

where y_t denotes the total output and Table (2) provides a full description of the model's parameters. The last term in equation (3.1) 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 productivity shock.[7] 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 vary over time. The law of motion for $\sigma_{\omega,t}$ is specified as follows

$$\sigma_{\omega,t} = \rho_{1,\sigma}\sigma_{\omega,t-1} + \rho_{2,\sigma}\sigma_{\omega,t-2} + \rho_{3,\sigma}\sigma_{\omega,t-3} + \sigma_{\sigma_\omega}\eta_t^\omega + \varkappa_{t-1} \tag{3.2}$$

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

$$\varkappa_t = \sigma_\varkappa \eta_t^\varkappa \tag{3.3}$$

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 optimising $\left(c_t^{opt}\right)$ and Rule of Thumb $\left(c_t^{RoT}\right)$ households

$$c_t = \phi_{RoT} c_t^{RoT} + (1 - \phi_{RoT}) c_t^{opt} \tag{3.4}$$

The consumption Euler equation for optimising is given by

$$\begin{aligned} c_t^{opt} &= \frac{\lambda/\gamma}{1+\lambda/\gamma} c_{t-1}^{opt} + \left(1 - \frac{\lambda/\gamma}{1+\lambda/\gamma}\right) \mathbb{E}_t c_{t+1}^{opt} + \frac{(\sigma_C - 1)\left(\bar{W}^h \bar{L}/\bar{C}\right)}{\sigma_C (1+\lambda/\gamma)} (l_t - \mathbb{E}_t l_{t+1}) \\ &- \frac{1-\lambda/\gamma}{\sigma_C (1+\lambda/\gamma)} (r_t - \mathbb{E}_t \pi_{t+1}) + \varepsilon_t^b \end{aligned} \tag{3.5}$$

where l_t is the hours worked, r_t is the nominal interest rate, π_t is the rate of inflation and $\varepsilon_t^b =$

[7] $G(\bar{\omega}, \sigma_\omega) = 1 - \Phi\left(\frac{0.5\sigma_\omega - log\bar{\omega}}{\sigma_\omega}\right)$ 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 $G(\bar{\omega}, \sigma_\omega)$ with respect to σ_ω.

$\rho_b\varepsilon_{t-1}^b + \sigma_b\eta_t^b$ is the consumption preference shock. If the degree of habits is zero ($\lambda = 0$), equation (3.5) reduces to the standard forward looking consumption Euler equation. The linearised investment equation is given by

$$i_t = \frac{1}{1+\beta\gamma^{1-\sigma_C}} i_{t-1} + \left(1 - \frac{1}{1+\beta\gamma^{1-\sigma_C}}\right) \mathbb{E}_t i_{t+1} + \frac{1}{\left(1+\beta\gamma^{1-\sigma_C}\right)\gamma^2\varphi} q_t + \varepsilon_t^i \tag{3.6}$$

where i_t denotes the investment and $\varepsilon_t^i = \rho_i\varepsilon_{t-1}^i + \sigma_i\eta_t^i$ is the investment efficiency shock. The sensitivity of investment to real value of the existing capital stock depends on the parameter φ (see, Christiano et al., 2005). The demand curve for new capital is given by

$$R_t^k = \pi_t + \frac{\bar{\pi}\bar{r}^k}{\bar{R}^k}\left(r_t^k + z_t\right) + \frac{(1-\delta)\,\bar{\pi}}{\bar{R}^k} q_t - q_{t-1} \tag{3.7}$$

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 define as

$$y_t = \phi_p\left(\alpha k_t^s + (1-\alpha)\, l_t + \varepsilon_t^a\right) \tag{3.8}$$

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

$$k_t = \frac{1-\delta}{\gamma} k_{t-1} + \frac{\gamma - 1 + \delta}{\gamma}\left(i_t + \gamma^2\varphi\varepsilon_t^i\right) \tag{3.9}$$

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

$$\begin{aligned} \pi_t = {} & \frac{i_p}{1+\beta\gamma^{1-\sigma_C} i_p}\pi_{t-1} + \frac{\beta\gamma^{1-\sigma_C}}{1+\beta\gamma^{1-\sigma_C} i_p}\mathbb{E}_t\pi_{t+1} \\ & - \frac{1}{\left(1+\beta\gamma^{1-\sigma_C} i_p\right)} \frac{\left(1-\beta\gamma^{1-\sigma_C}\xi_p\right)\left(1-\xi_p\right)}{\left(\xi_p\left(\left(\phi_p - 1\right)\varepsilon_p + 1\right)\right)}\mu_t^p + \varepsilon_t^p \end{aligned} \tag{3.10}$$

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 the price mark-up price shock which is assumed to be an ARMA(1,1) process. Monopolistic competition in the labour market also gives rise to a similar wage New-Keynesian Phillips curve

$$\begin{aligned} w_t = {} & \frac{1}{1+\beta\gamma^{1-\sigma_C}} w_{t-1} + \frac{\beta\gamma^{1-\sigma_C}}{1+\beta\gamma^{1-\sigma_C}}\left(\mathbb{E}_t w_{t+1} + \mathbb{E}_t\pi_{t+1}\right) - \frac{1+\beta\gamma^{1-\sigma_C} i_w}{1+\beta\gamma^{1-\sigma_C}}\pi_t \\ & + \frac{i_w}{1+\beta\gamma^{1-\sigma_C}}\pi_{t-1} - \frac{1}{1+\beta\gamma^{1-\sigma_C}} \frac{\left(1-\beta\gamma^{1-\sigma_C}\xi_w\right)\left(1-\xi_w\right)}{\left(\xi_w\left(\left(\phi_w - 1\right)\varepsilon_w + 1\right)\right)}\mu_t^w + \varepsilon_t^w \end{aligned} \tag{3.11}$$

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

$$B_t = \frac{\bar{K}}{\bar{B}}\left(q_t + k_t\right) - \frac{\bar{K}-\bar{B}}{\bar{B}} n_t \tag{3.12}$$

where n_t stands for entrepreneur's networth. The following two equations are the linearised entrepreneurs' first order conditions with respect to lagrange multiplier and leverage, respectively

$$\begin{aligned} B_t &= R_t^k - r_{t-1} + q_{t-1} + k_{t-1} \\ &+ \frac{1}{\Gamma\left(\bar{\omega},\bar{\sigma}_\omega\right) - \mu G\left(\bar{\omega},\sigma_\omega\right)} \left(\begin{array}{c} \frac{\partial\left[\Gamma(\bar{\omega},\sigma_\omega) - \mu G(\bar{\omega},\sigma_\omega)\right]}{\partial\omega}\bar{\omega}\omega_t \\ + \frac{\partial\left[\Gamma(\bar{\omega},\bar{\sigma}_\omega) - \mu G(\bar{\omega},\sigma_\omega)\right]}{\partial\sigma_\omega}\sigma_\omega\sigma_{\omega,t} \end{array} \right) \end{aligned} \tag{3.13}$$

$$\begin{aligned} E_t R_{t+1}^k &= r_t + \left(\frac{\frac{\partial\varrho(\bar{\omega},\sigma_\omega)}{\partial\omega}}{\varrho\left(\bar{\omega},\sigma_\omega\right)} + \frac{\frac{\partial\Gamma(\bar{\omega},\sigma_\omega)}{\partial\omega}}{1-\Gamma\left(\bar{\omega},\sigma_\omega\right)} \right)\bar{\omega}\omega_{t+1} \\ &+ \left(\frac{\frac{\partial\varrho(\bar{\omega},\bar{\sigma}_\omega)}{\partial\sigma_\omega}}{\varrho\left(\bar{\omega},\bar{\sigma}_\omega\right)} + \frac{\frac{\partial\Gamma(\bar{\omega},\sigma_\omega)}{\partial\sigma_\omega}}{1-\Gamma\left(\bar{\omega},\sigma_\omega\right)} \right)\sigma_\omega\sigma_{\omega,t+1} + n_t - q_t - k_t \end{aligned} \tag{3.14}$$

where r_t is the nominal interest rate and

$$\Gamma\left(\bar{\omega},\bar{\sigma}_\omega\right) = \bar{\omega}\left(1 - F\left(\bar{\omega},\sigma_\omega\right)\right) + G\left(\bar{\omega},\sigma_\omega\right) \tag{3.15}$$

$$\varrho\left(\bar{\omega},\bar{\sigma}_\omega\right) = \frac{1 - F\left(\bar{\omega},\sigma_\omega\right)}{1 - F\left(\bar{\omega},\sigma_\omega\right) - \mu\bar{\omega}\frac{\partial F(\bar{\omega},\sigma_\omega)}{\partial\omega}} \tag{3.16}$$

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

$$\begin{aligned} n_t &= \frac{\bar{\varsigma}}{\gamma\bar{\pi}}\left(\frac{\left(1-\mu G\left(\bar{\omega},\sigma_\omega\right)\right)\bar{R}^k}{1-\frac{\bar{B}}{\bar{K}}} - \frac{\bar{r}\frac{\bar{B}}{\bar{K}}}{1-\frac{\bar{B}}{\bar{K}}} \right)\varsigma_t + \frac{\bar{\varsigma}}{\gamma\bar{\pi}}\frac{\left(1-\mu G\left(\bar{\omega},\sigma_\omega\right)\right)\bar{R}^k}{1-\frac{\bar{B}}{\bar{K}}}\left(R_t^k + q_{t-1} + k_{t-1}\right) \\ &- \frac{\bar{\varsigma}}{\gamma\bar{\pi}}\frac{\bar{R}\frac{\bar{B}}{\bar{K}}}{1-\frac{\bar{B}}{\bar{K}}}\left(r_{t-1} + B_{t-1}\right) - \frac{\bar{\varsigma}}{\gamma\bar{\pi}}\frac{\mu\bar{R}^k}{1-\frac{\bar{B}}{\bar{K}}}\left(\frac{\partial G\left(\bar{\omega},\sigma_\omega\right)}{\partial\omega}\omega\omega_t + \frac{\partial G\left(\bar{\omega},\sigma_\omega\right)}{\partial\sigma_\omega}\sigma_\omega\sigma_{\omega,t} \right) \end{aligned} \tag{3.17}$$

where $\varsigma_t = \rho_\varsigma\varsigma_{t-1} + \sigma_\varsigma\eta_t^\varsigma$ is the fraction of the entrepreneurs that dies. The consumption of non-optimising agents is given by

$$c_t^{RoT} = \frac{\bar{W}^h\bar{L}}{\bar{C}}\left(w_t + l_t\right) - \frac{\bar{Y}}{\bar{C}}trans_t \tag{3.18}$$

The following equation describe the evolution of debt

$$d_t = \bar{R}\left(\frac{1}{\bar{\pi}}d_{t-1} + \varepsilon_t^g - trans_t\right) \tag{3.19}$$

and transfers are given by

$$trans_t = \phi_d d_{t-1} + \phi_g\varepsilon_t^g \tag{3.20}$$

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

$$r_t = \rho r_{t-1} + (1-\rho)\left[r_\pi\pi_t + r_y\left(y_t - y_t^p\right)\right] + r_{\Delta y}\left[\left(y_t - y_t^p\right) + \left(y_{t-1} - y_{t-1}^p\right)\right] + \varepsilon_t^r \tag{3.21}$$

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 the monetary policy shock.[8]

3.2 Minimum Distance Estimation

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.[9] 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.

In brief, we find the vector of DSGE parameters that minimises 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 et al. (2005) and Altig et al. (2011). These methods have well documented costs and benefits relative to full information methods, which we summarise 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 hope to 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 tests 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.[10]

Collecting all the VAR variable responses after a risk news shock for all periods in one vector, say, $\widehat{\mathcal{R}}$ and doing the same for the DSGE ones, $\mathcal{R}(\theta)$, then we can select the structural parameter vector that minimises the following norm:

$$\theta = \arg\min \left(\widehat{\mathcal{R}} - \mathcal{R}(\theta)\right)' \mathcal{W} \left(\widehat{\mathcal{R}} - \mathcal{R}(\theta)\right) \tag{3.22}$$

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.

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). Estimates of all parameters, and the identify of those that are calibrated is reported in Table 2. Chart 11 plots the impulse response to a risk news shock comparing the VAR with the DSGE model at the minimum distance estimates.

[8]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.

[9]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.

[10]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.

As we see, the DSGE model can be made to fit may 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 is that our minimum distance estimates suggest that the portion of consumers that are living hand-to-mouth is 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 minimum distance estimates choose a high proportion of hand to mouth consumers to turn off a good deal of this intertemporal consumption substitution by rational consumers. The contrasting responses of the model with and without hand to mouth consumers are illustrated by Charts 13 and 14. Here we plot the responses to a risk news shock for two versions of the DSGE model: one with the estimated 75% of hand to mouth consumers, and one with 100% 'rational' or unconstrained, with all other parameters at the calibrated/minimum distance estimated values reported in Table 2. It is very clear that the two models are very different here too. The charts show how different having a large portion of hand-to-mouth 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 hand-to-mouth considers generates much larger falls in hours worked and inflation. This is despite the much larger cut in the central bank interest rate that is estimated to occur. All this said, it is important to recognise that the linearised DSGE model we work with here rules out factors like precautionary saving. What the minimum distance estimation interprets as rule of thumb 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 minimum distance 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 the bankruptcy cost, the more we weaken the financial accelerator mechanism in the model, and it instead converges on and environment without financial frictions, in which fluctuations in risk, and revelations about future such fluctuations, would have no effect (in this linearised model) on anything else. In chart 15, 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 at this calibration shrink the estimated variance of the shocks, as can be seen by the fact that the impulse response of the risk (labelled 'volatility' in the Chart) series shrinks toward the VAR estimated response, leaving the performance of the other impulse responses (how far they lie from the VAR responses) pretty much 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 of our MDE to 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 hand-to-mouth consumers. Using CMR values 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.

4 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 shocks 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 (recall we had quarterly data from 1980-2010). Figure 12 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. These corroborate BS finding that their original scheme was able to recover news shocks to TFP in data generated from an RBC model.[11] That the scheme works well seems to be very robust to different choices of h.

5 Conclusion

This paper took as its starting point recent work by Christiano et al. (2013) (CMR). They used a DSGE model with financial frictions that articulated a risk news shock (revelations today about changes in the variance of idiosyncratic returns that would take place in the future) and full information methods to deduce that contemporaneous and risk news shocks together contributed around 60% to business cycle fluctuations in output in the US. The shocks they back out correlate well with a measure of the time series of the dispersion in US corporate stock returns.

We take a different, complementary approach. We identify risk news shocks in a VAR. To do this, we take two proxies for the time series of idiosyncratic private sector risk (the VIX, and the interquartile

[11] 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 successfully.

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. The original BS work sought to identify news in TFP. In their work a news shock to TFP was something that left today's TFP unaffected but contributed maximally to TFP forecast errors at some horizon in the future. Analogously, our risk news shock is a shock that leaves the risk proxy unchanged today, but contributes maximally at some horizon in the future. In monte carlo tests in a laboratory constructed to resemble precisely the DSGE model that we subsequently fit to these identified VAR responses, we find that the scheme works very well in recovering the shocks and responses.

We find that revelations about future increases in risk cause output, consumption, investment, hours worked and inflation all to fall, despite a vigorous and protracted cut in central bank interest rates, and is associated with a rise in spreads. Comparing like for like, risk news shocks have much larger effects than contemporaneous risk shocks, which are also identified in our scheme. These results survive using both our proxies for risk. 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.

Finally, we try to fit a DSGE model to the VAR identified impulse responses to a risk news shock. We use a DSGE model comprising the features of Smets and Wouters (2007) with Bernanke et al. (1999) financial frictions and allowing for the possibility that a portion of consumers live hand-to-mouth as in Gali et al. (2007). 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 live hand-to-mouth. Without hand-to-mouth consumers (holding other parameters constant at their minimum distance estimates) 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.

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A Charts

Figure 1: Risk Shock

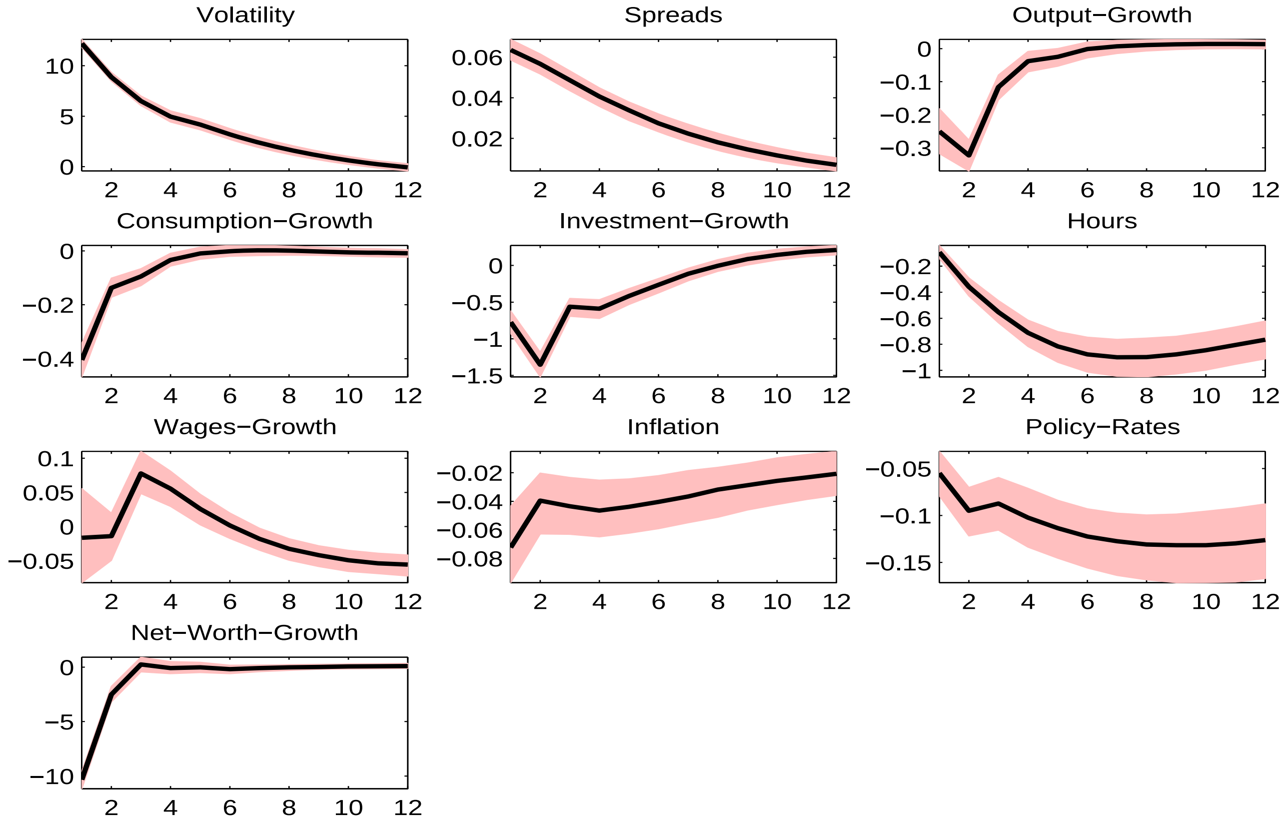


Figure 2: Risk Shock

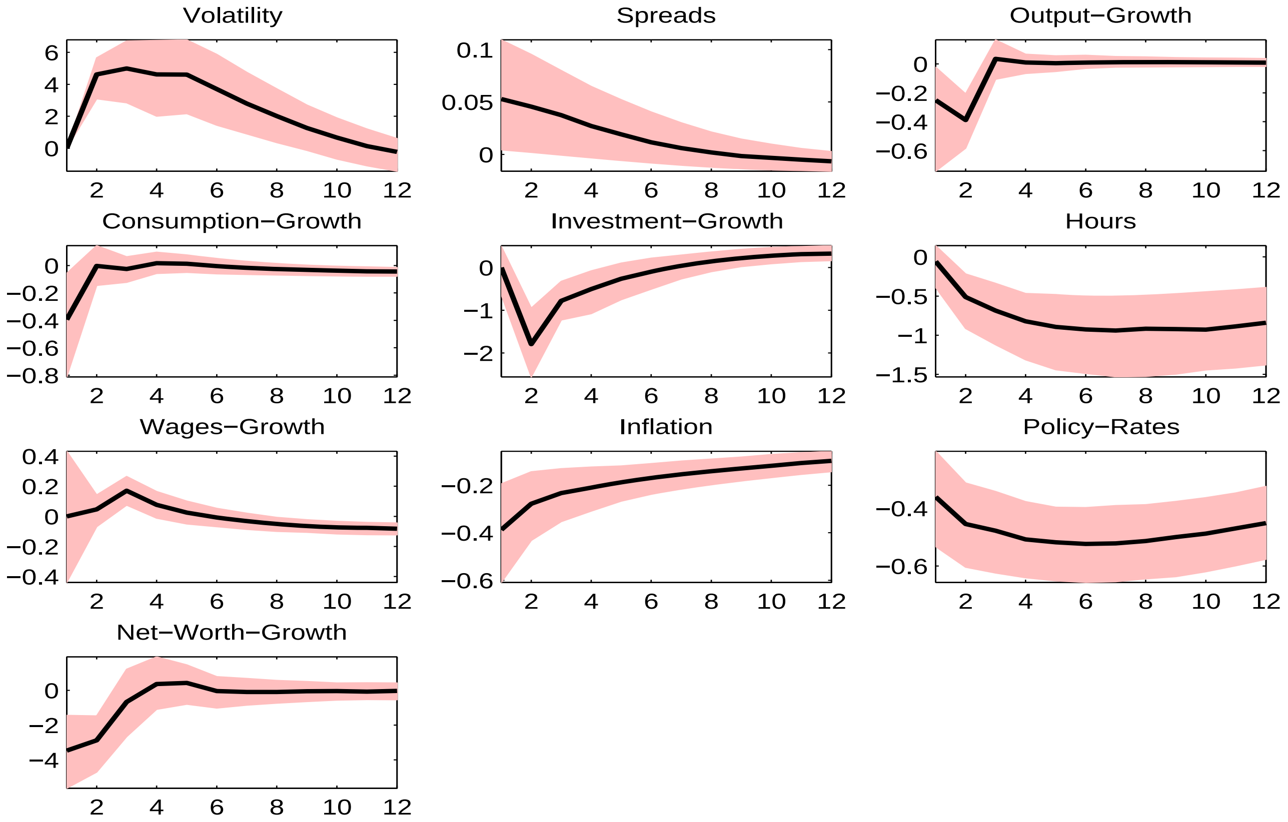


Figure 3: Supply Shock

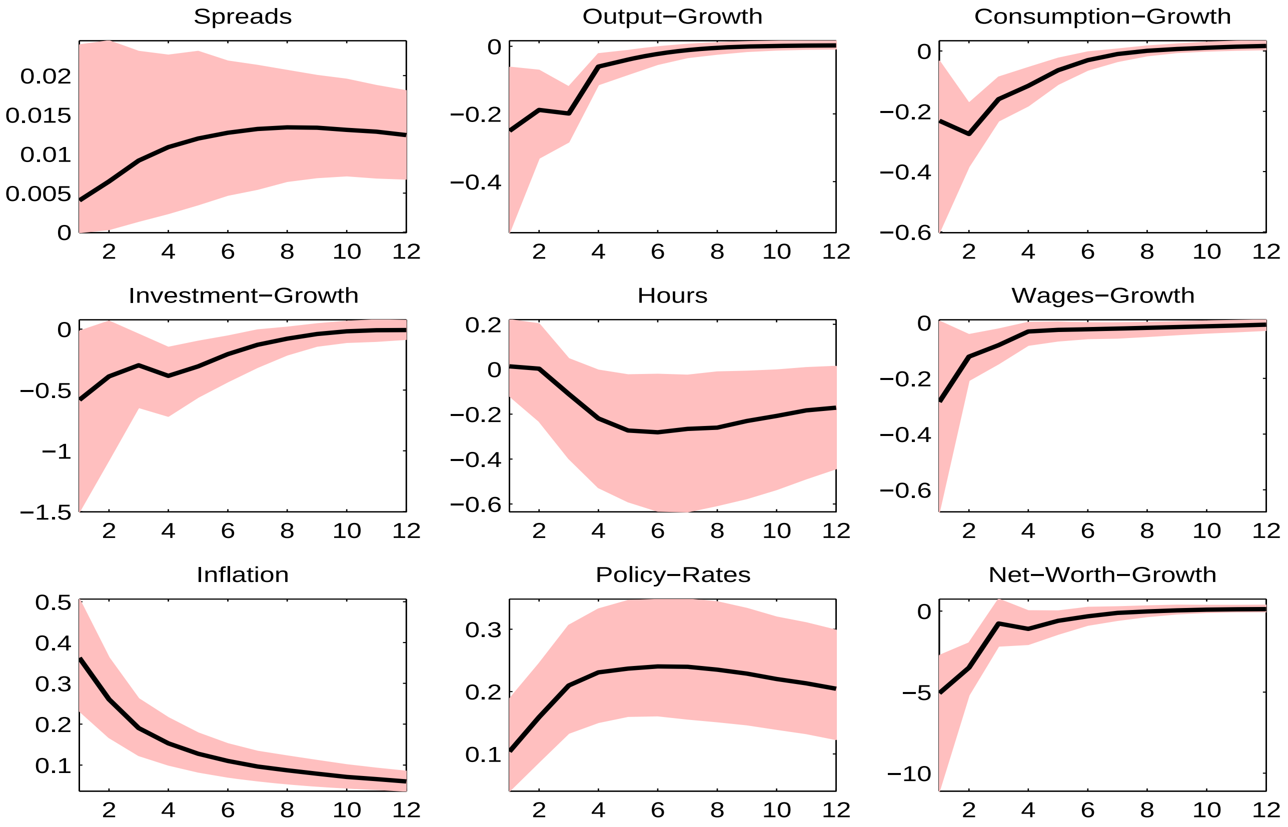


Figure 4: Demand Shock

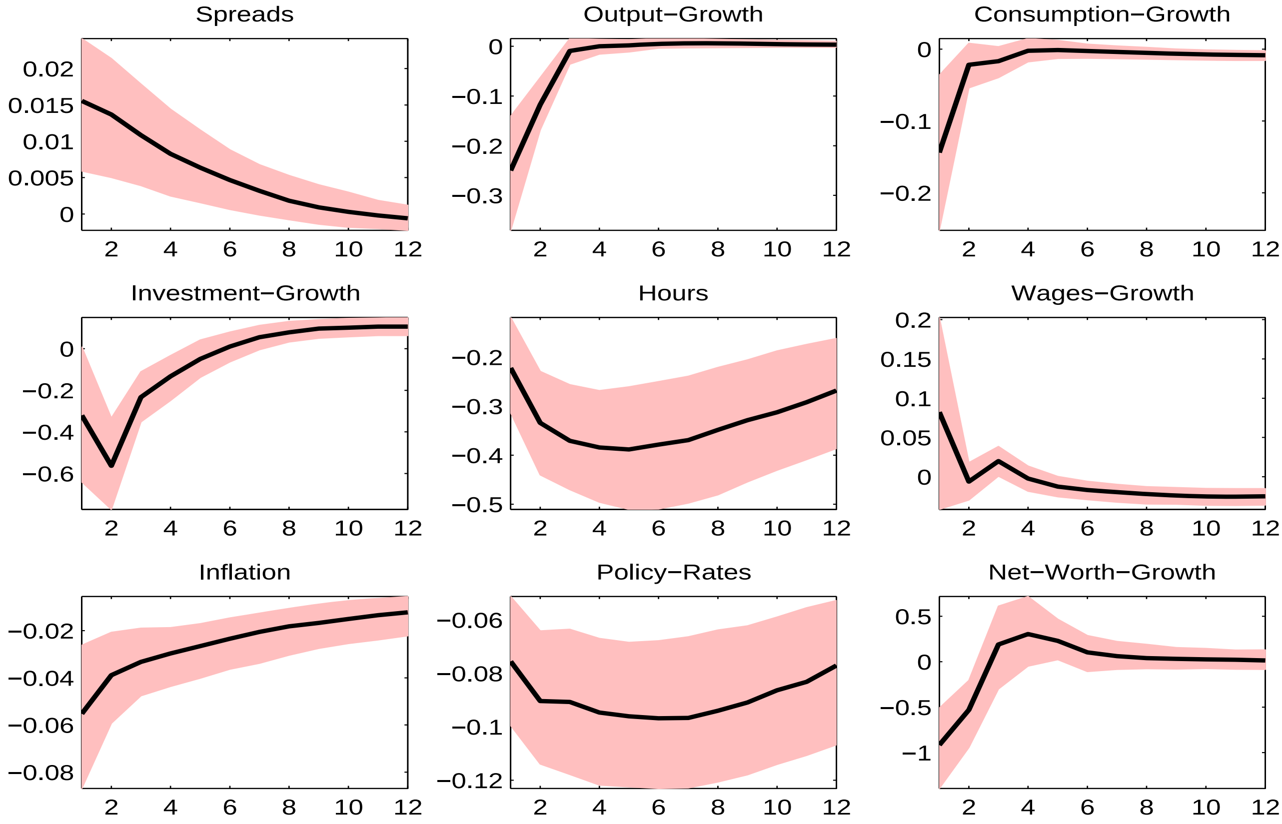


Figure 5: Monetary Policy Shock

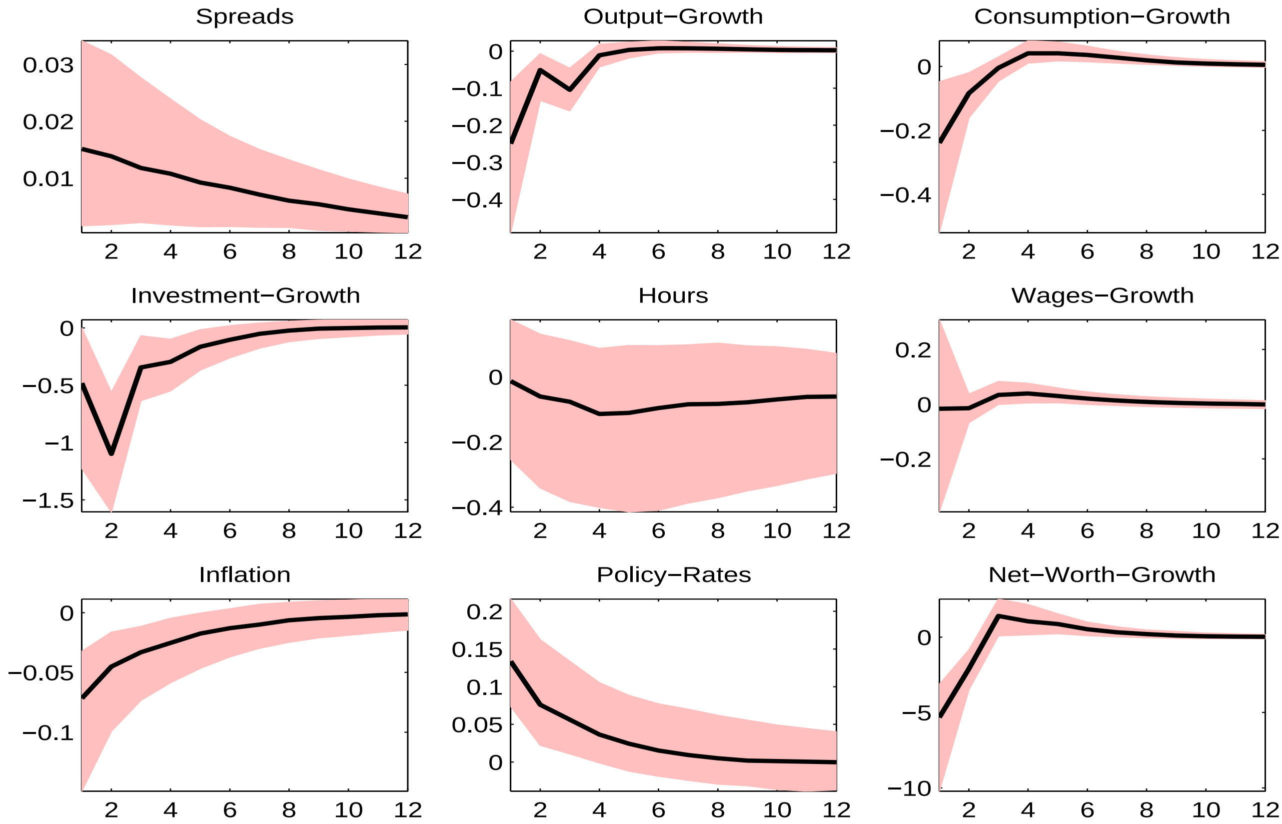


Figure 6: Historical Decomposition Between 2007$Q1$ – 2010$Q2$

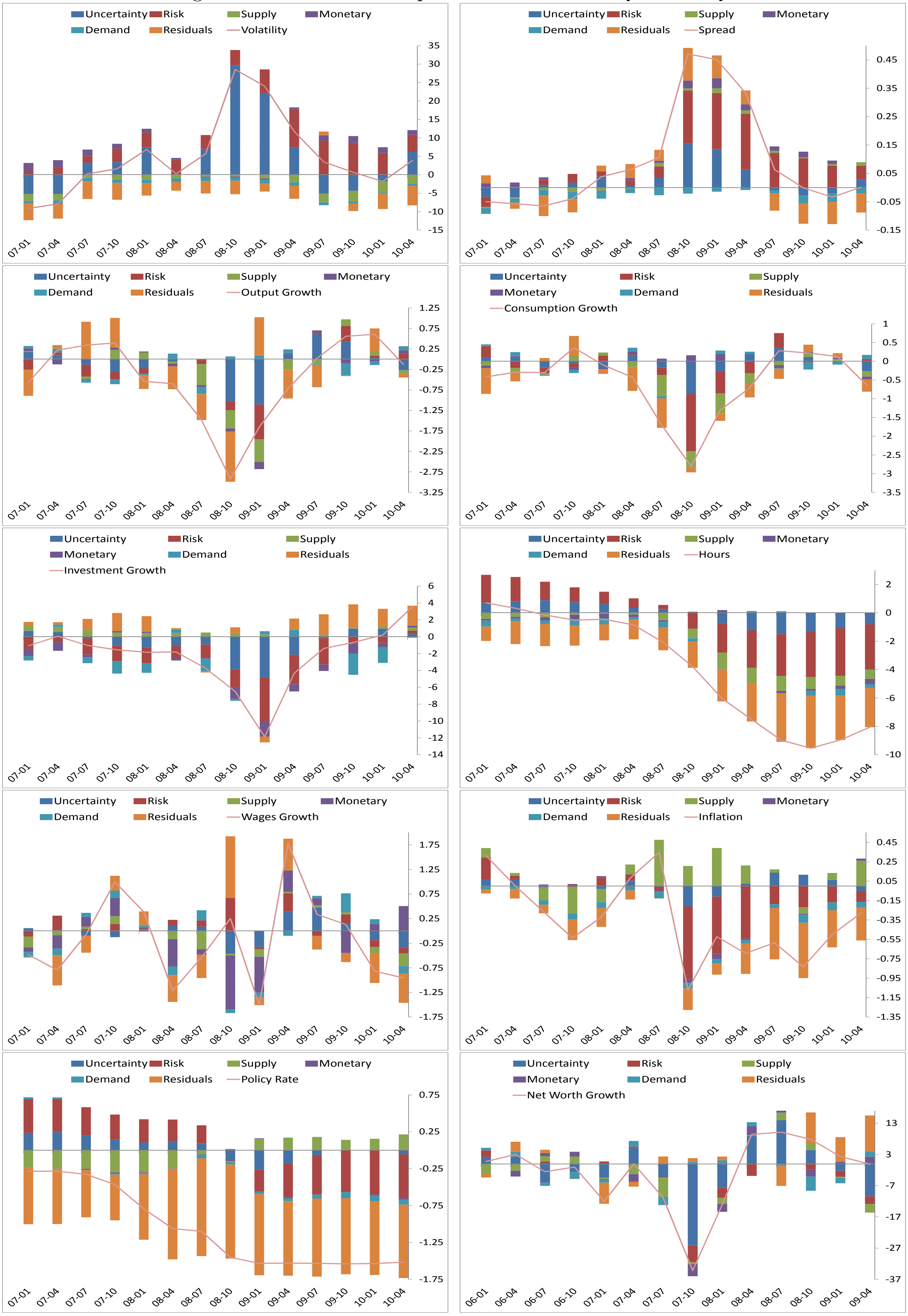


Figure 7: Forecast Variance Decomposition: VIX

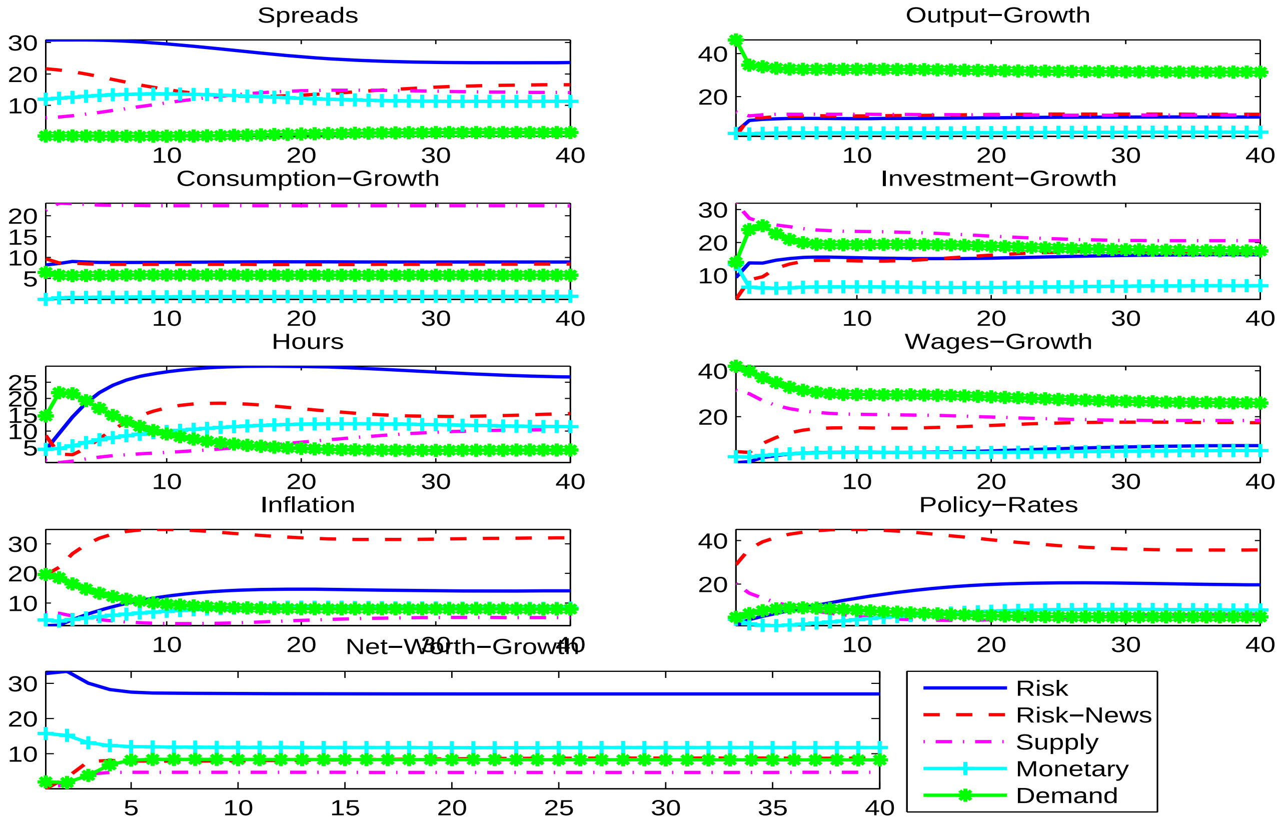


Figure 8: Uncertainty versus Risk Shock

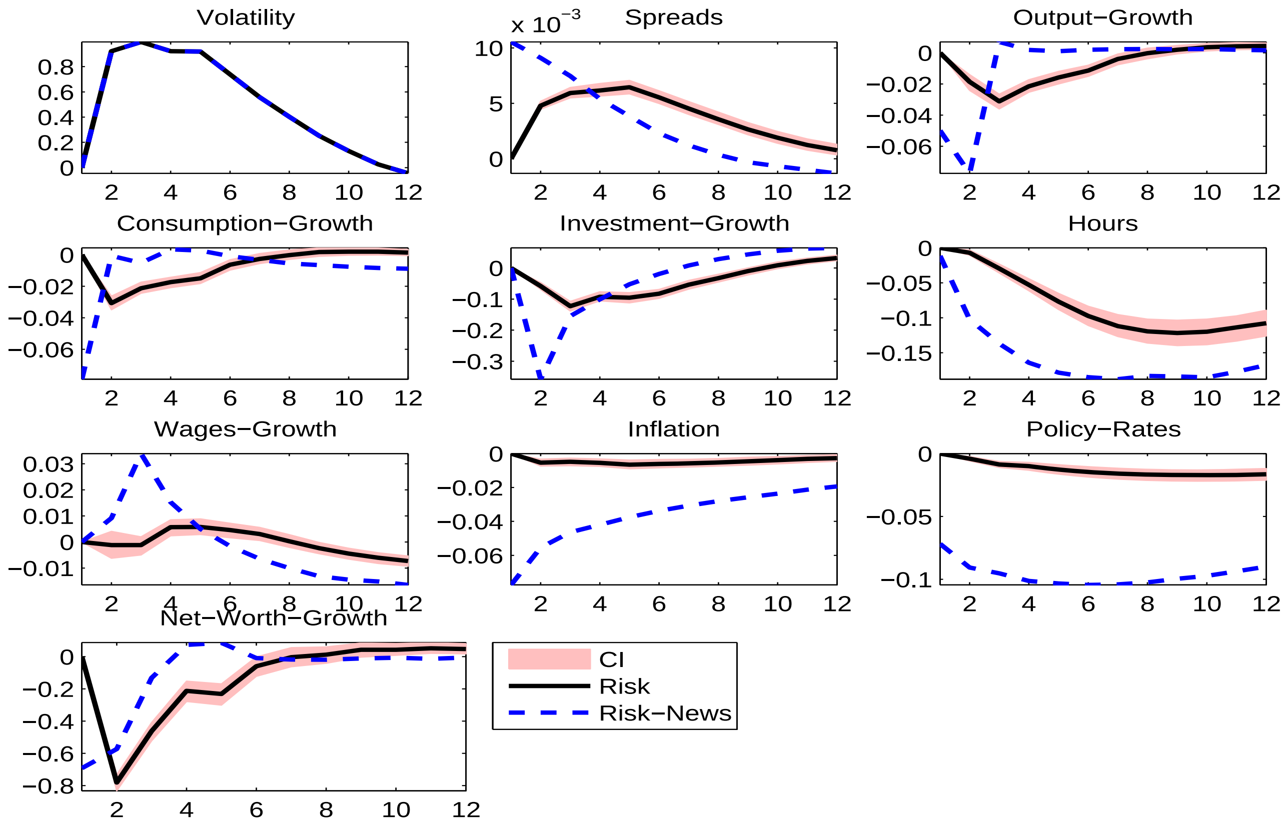


Figure 9: Forecast Variance Decomposition: Cross-Section

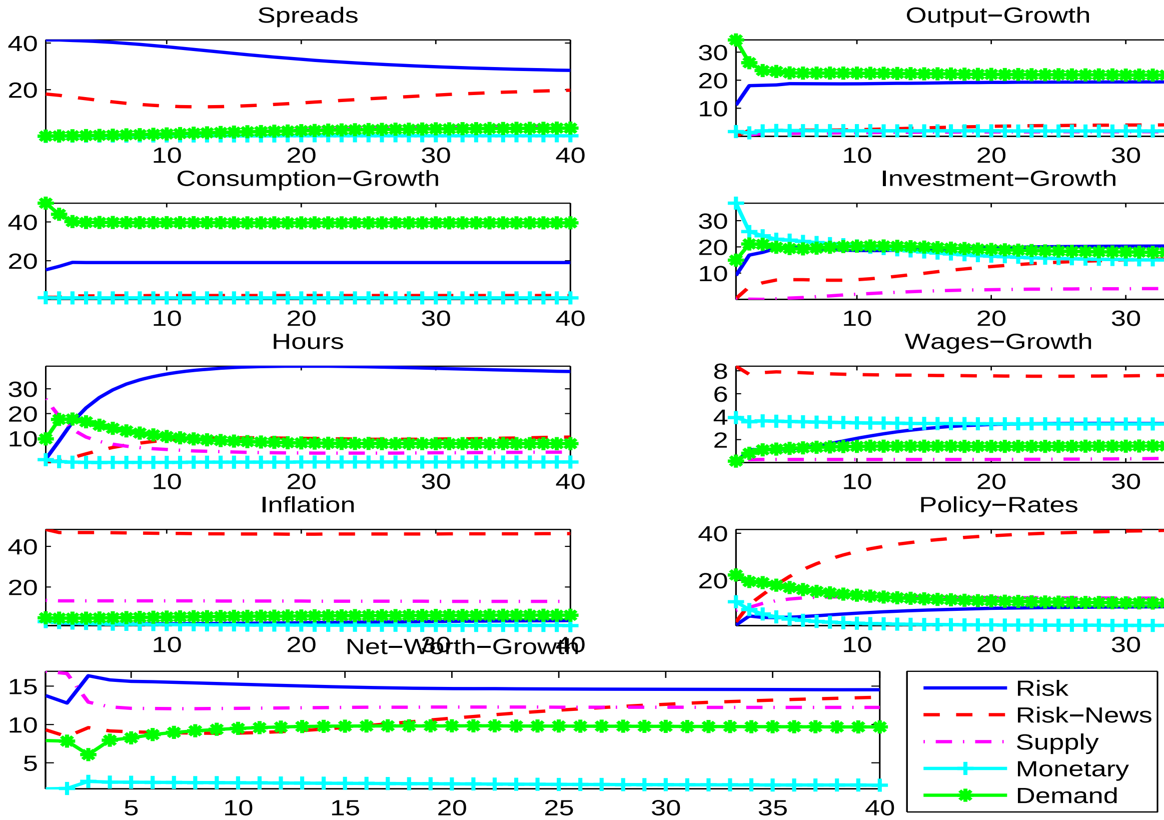


Figure 10: Cross Section versus VIX Volatility: Risk News Responses

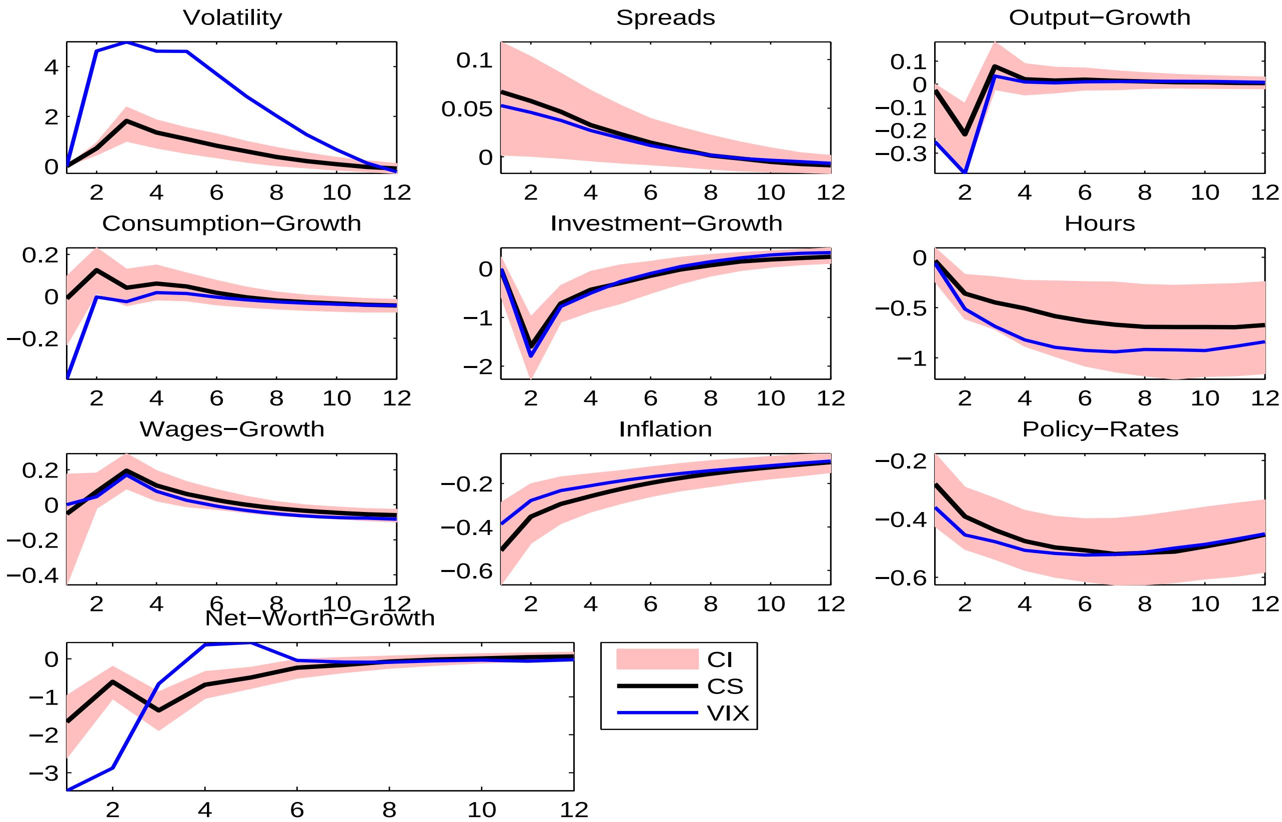


Figure 11: DSGE Model Fit

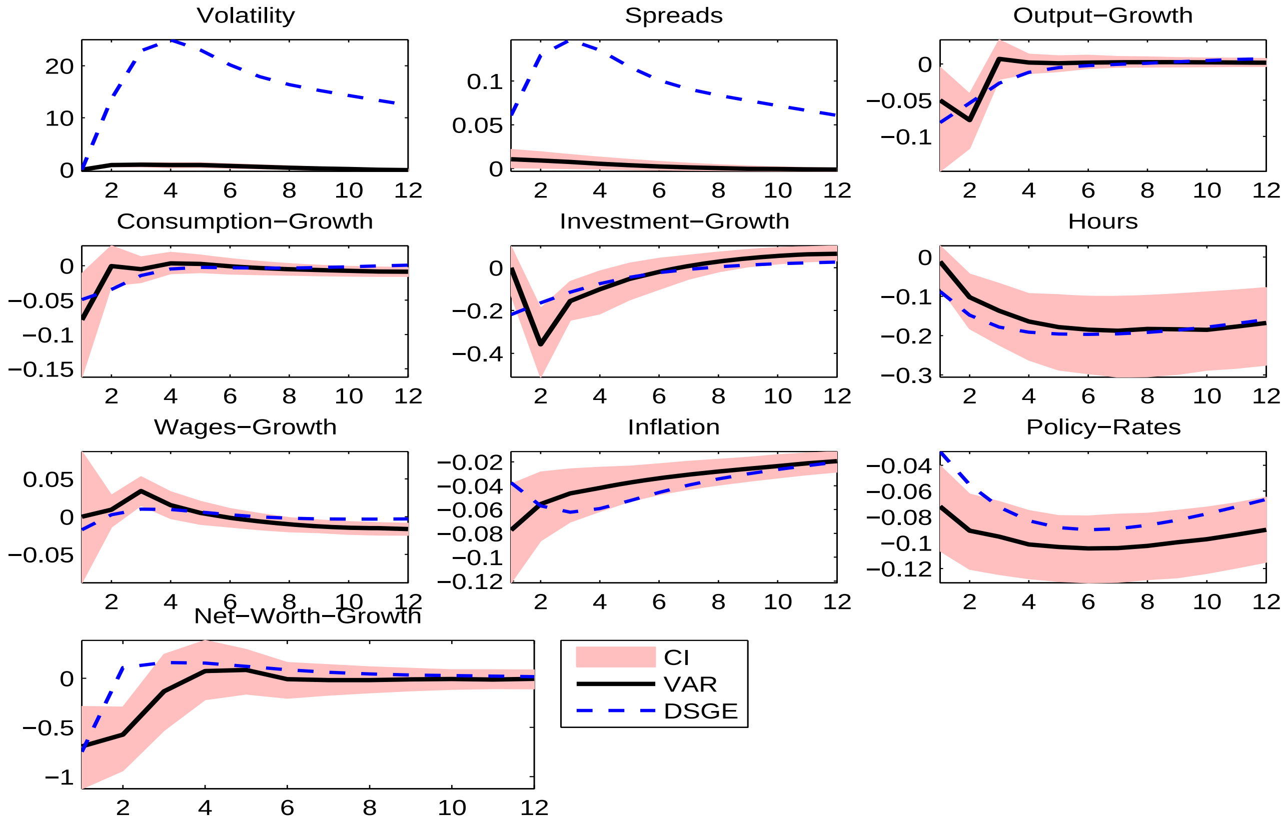


Figure 12: Monte Carlo Simulations

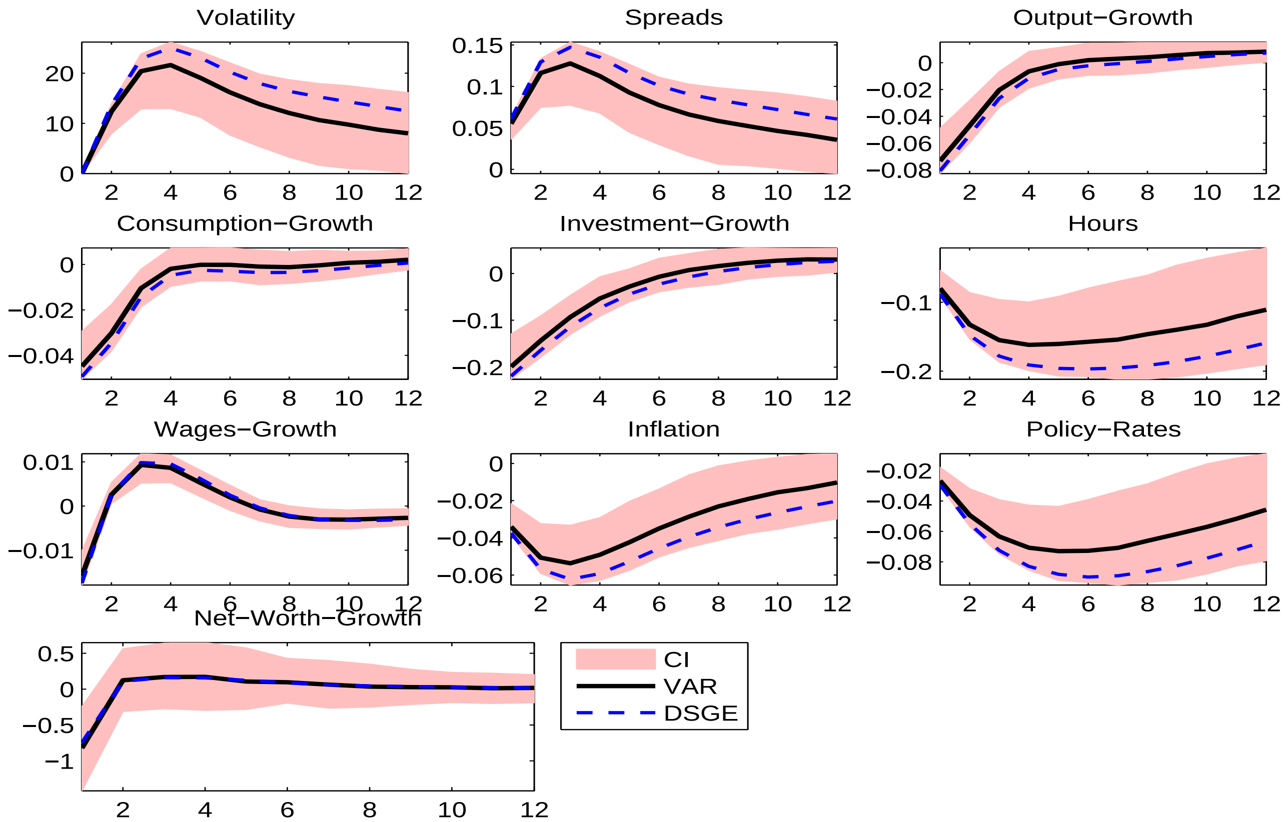


Figure 13: HtM versu No HtM Consumers: Risk Shock

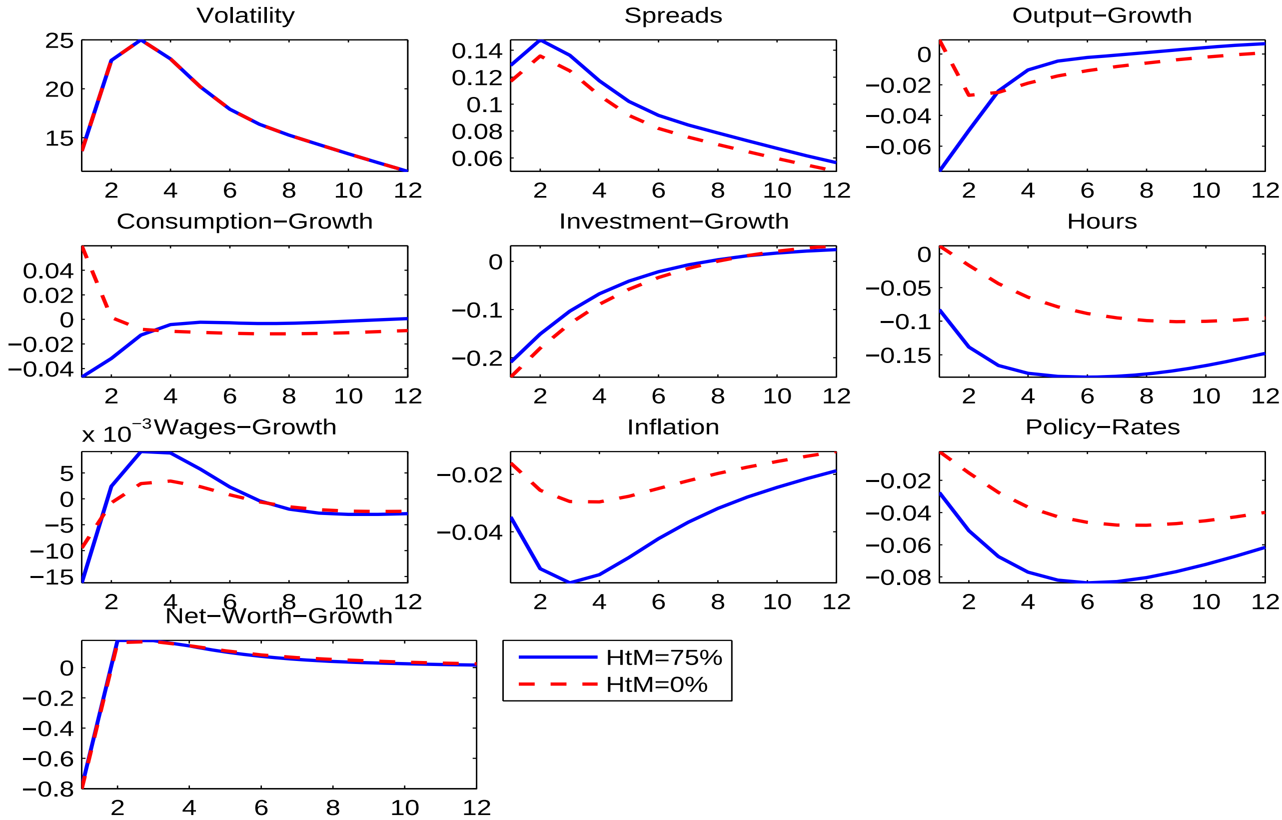


Figure 14: HtM versu No HtM Consumers: Risk News Shock

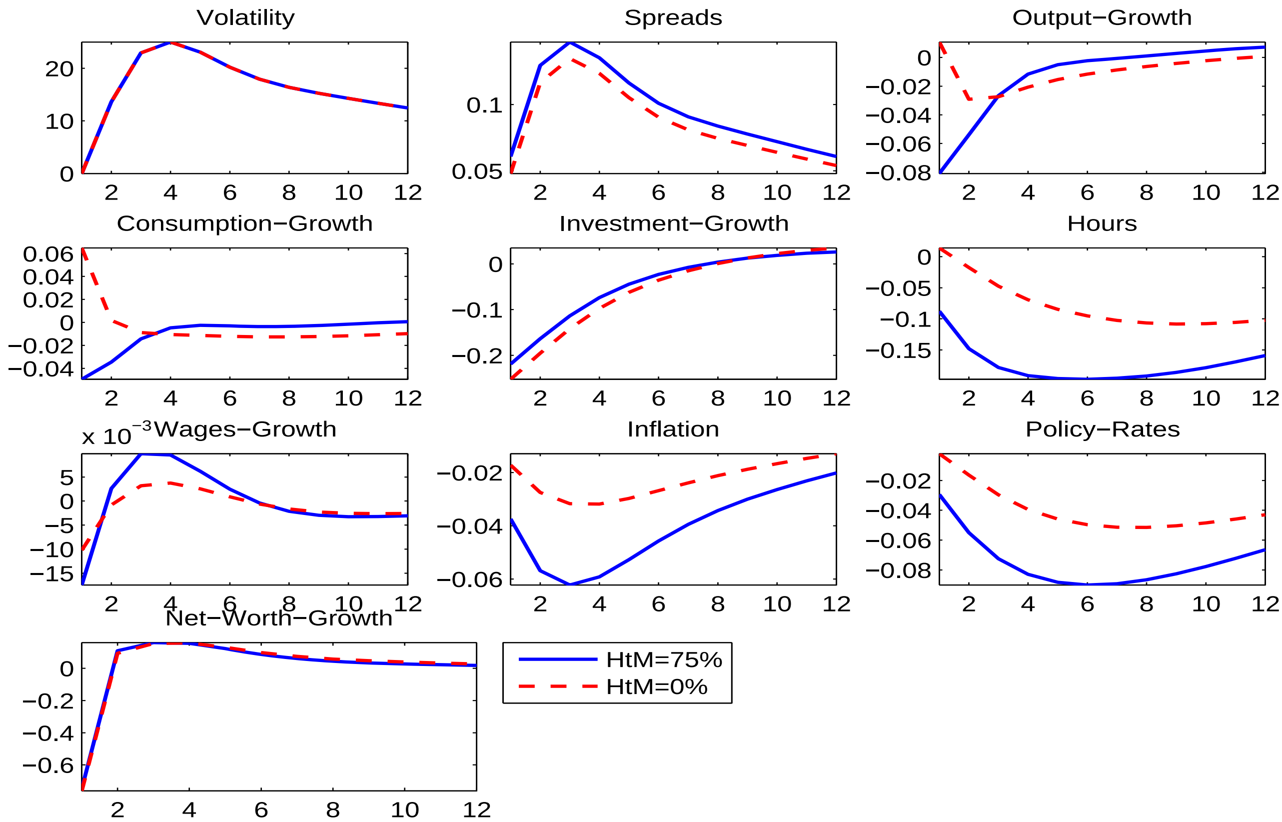
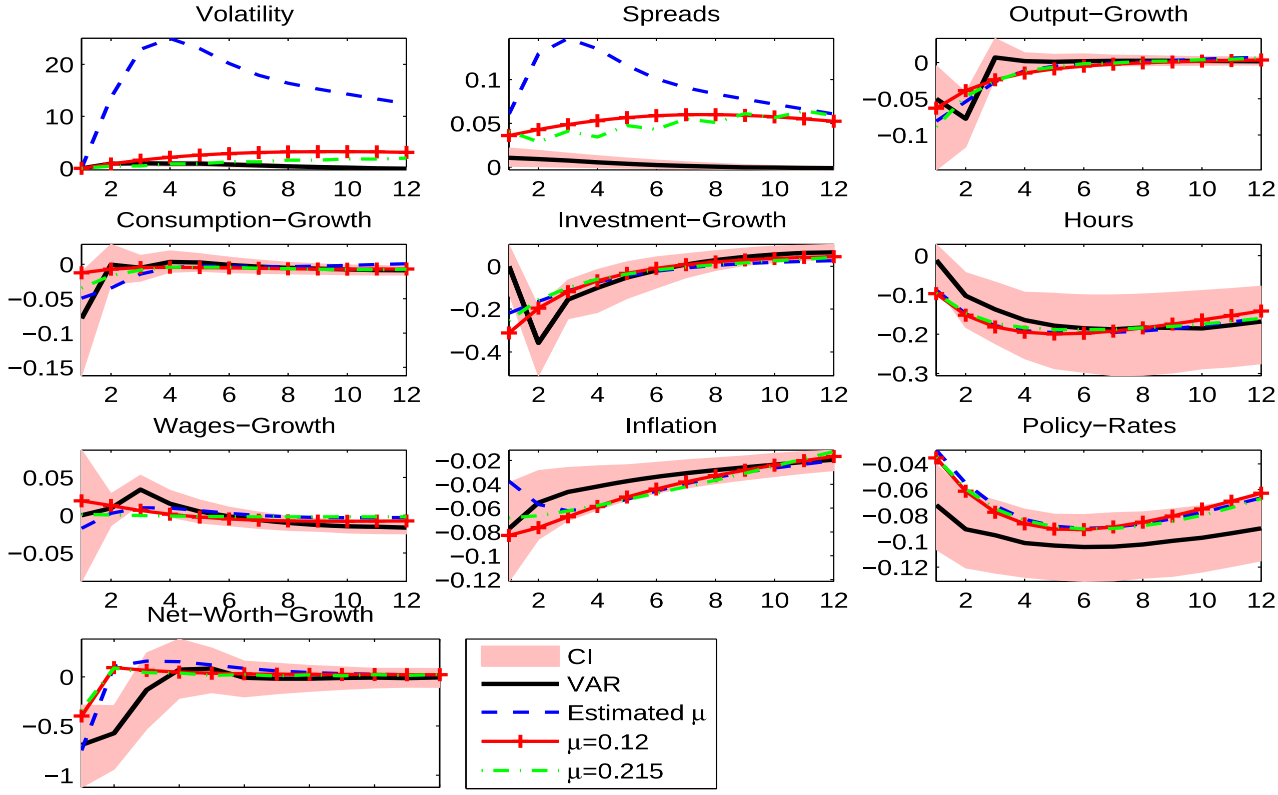


Figure 15: The relationship between the size of financial frictions and the magnitude of the shock



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)