September 15, 2016

Comment on Risk Shocks by Christiano, Motto, and Rostagno (2014)*

Abstract

In a recent paper, Christiano, Motto and Rostagno (2014, henceforth CMR) report that risk shocks are the most important source of business cycle fluctuations. This result is in contrast to much of the existing literature; e.g. Bachmann and Bayer (2013) report that risk shocks account for 4% of the volatility in GDP. We resolve this apparent contradiction by first highlighting that CMR depart from the normal definition of a risk shock by including an additional "news" component. We then incorporate their definition of risk shocks into a canonical financial accelerator model that does not include the array of rigidities (both nominal and real) that are in the model economy employed by CMR. In the base model, risk shocks as normally defined play a quantitatively minor role in business cycle activity; however, when the CMR definition is employed, we replicate their result that risk shocks are the most important impulse mechanism of business cycles. It is clear from this analysis that the endogenous amplification and propagation mechanisms in the CMR model do not account for the significant role that risk shocks play in fluctuations; rather, it is the exogenous definition of risk shocks that is doing virtually all of the work. We conclude that the CMR finding should be viewed with caution.

- *JEL Classification: E4, E5, E2*
- Keywords: *agency costs, credit channel, time-varying uncertainty.*

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*Gabriel Lee and Johannes Strobel gratefully acknowledge financial support from the German Research Foundation ((DFG) LE 1545/1-1).

1 Introduction

Christiano, Motto and Rostagno (2014, henceforth CMR) augment the Bernanke-Gertler-Gilchrist financial accelerator model with New Keynesian features (*à la* Christiano, Eichenbaum and Evans (2005)) to show the importance of cross-sectional idiosyncratic uncertainty (risk) for the business cycle. CMR find, among other results, their risk shocks are the most important driver of the business cycle, accounting for 62% of the variation in output in the business cycle frequency. CMRs results, however, contradicts other recent papers, such as Bachmann and Bayer (2013), Chugh (2016) or Dmitriev and Hoddenbagh (2014), and Dorofeenko, Lee and Salyer (2008, 2014), that show risk shocks play a small or no role for business cycle fluctuations of real variables.

Figure 1: Normalized cyclical components of uncertainty (risk) shocks in the literature. The shocks are i) the Macro uncertainty by Jurado, Ludvigson and Ng (2015), ii) the VIX used by Bloom (2009), iii) policy uncertainty by Baker, Bloom and Davis (2012), iv) the U.S. construction risk by Dorofeenko, Lee and Salyer (2014), v) and the uncertainty measure implied by the model of CMR.

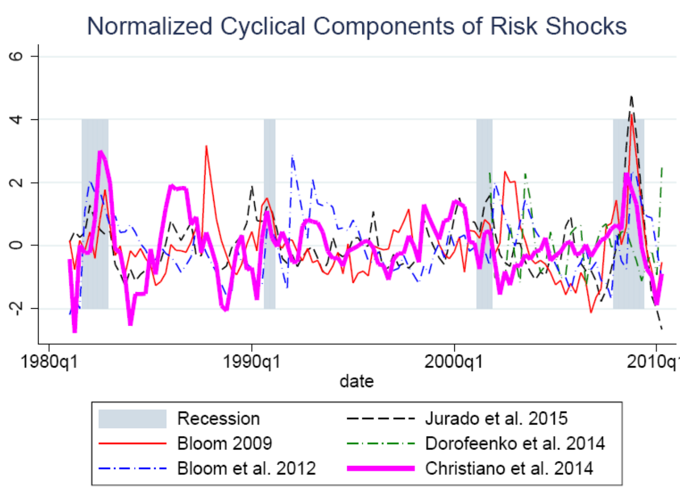

Figure 1 shows the normalized cyclical components of various risk shocks after HP-filtering. The magnitude of risk shocks implied by CMR's model, in comparison to the empirical measures in Figure 1, is equal if not smaller than the others in the period from 1990 to 2012. The question then arises as to why there is a large difference of findings between CMR and others. The objective of this note is to show that CMRs results are potentially misleading. We show that it is important to distinguish between risk shocks and risk *news* shocks.

Unlike in the standard business cycle model, where agents do not learn about a shock until it occurs, CMR introduce a *news* component to uncertainty shocks such that agents receive signals about a shock ahead of the realization. In CMR model, the strength of the signal increases over time. Agents receive the first signal eight quarters before a shock occurs, i.e. eight quarters before there is a change in the level of risk. The magnitude of signals ranges from 2.83% to 4.25% per period and culminate to a 10.52% innovation. We argue in this paper that the magnitude and the length of signals are a likely explanation for accounting the different findings between CMR and others.

To demonstrate our point, we use the risk shocks due to CMR into a simple financial accelerator model of Dorofeenko, Lee and Salyer (2008, henceforth DLS) with no New Keynesian features.[1] Within our simple framework, as in CMR, we also find that risk shocks *à la* CMR explain 53.94% of the variation in output, while a standard 1% innovation to unanticipated risk, as in DLS, only explains 0.7% of the variation in output. As an additional benchmark, we also present the effects of a 7% (unanticipated) innovation to risk in the absence of the *news* component. An increase of 1% to 7% innovation to risk, we show that a simple financial accelerator model without further frictions in economy can explain 25.80% of the variation in output is due to unanticipated risk. Our results suggest the main driver of the different impact of risk shocks in financial accelerator models is due to the combination of the magnitude of the innovation and the presence of a *news* component, rather than due the propagation mechanism of CMR's model.

[1] The variation explained by risk shocks containing the news component is potentially overstated, see Sims (2016). We do not further discuss potential conceptual issues of using variance decompositions and news shocks raised by Sims (2016) but briefly summarize the issue.

CMR distinguish between unanticipated and anticipated innovations to risk, with the latter innovations also referred to as news component. Sims (2016) points out that it is not entirely clear how important pure news (the impact of signals on choices before there actually is a change in the state variable) relative to realized news (realized changes in fundamentals that were anticipated in the past) are.

2 Comparing Risk Shocks

2.1 Modeling Innovations to Risk

We briefly outline the risk shock structure as in DLS, who modify the financial accelerator model of Carlstrom and Fuerst (1997) by varying the second moment of entrepreneurs' productivity distribution over time; $\sigma_\omega = \sigma_{\omega,t}$. More precisely, in DLS, $\log(\sigma_{\omega,t})$ follows an autoregressive process of order one

$$\log(\sigma_{\omega,t}) = (1-\rho_{\sigma_\omega})\log(\bar{\sigma}_\omega) + \rho_{\sigma_\omega}\log(\sigma_{\omega,t-1}) + u_t \quad (1)$$

$$u_t \sim i.i.d. \quad (2)$$

with $\bar{\sigma}_\omega$ the steady state level of uncertainty. CMR replace (2) by introducing an anticipated, or *news* component to the innovation, such that

$$u_t = \xi_{0,t} + \xi_{1,t-1} + ... + \xi_{p,t-p}. \quad (3)$$

CMR assume that in period t, agents observe signals $\xi_{j,t}$, $j = 0, 1, ...p$, which are correlated over time. Moreover, $j > 0$ is refers to the index of the anticipated, or *news* component of u_{t+j}, while $\xi_{0,t}$ reflects the unanticipated innovation. We compute the magnitude of a signal, $\log(\xi_i)$, based on the `Dynare` code of CMR as

$$\log(\xi_i) = \rho_{\sigma,n}^{p-i}\sigma_{\sigma,n}e_{\xi_p} + \sum_{j\in\mathbb{N},p>j\geqslant i}^{p-1}\sqrt{1-\rho_{\sigma,n}^2}\sigma_{\sigma,n}\rho_{\sigma,n}^{j-i}e_{\xi_j} \text{ for } i > 0 \quad (4)$$

where $\sigma_{\sigma,n}$ is the standard deviation of the anticipated risk shock, $\rho_{\sigma,n}$ is the correlation among signals of the risk shock and e_{ξ_i} is binary variable, indicating the occurrence of a signal ξ_i.

Given the above set up of $\log(\xi_i)$, consider a risk *news* shock where agents obtain the first signal eight quarters ahead of the actual innovation. In this case, $p = 8$ and the magnitude of the

Table 1: Parameter values of the unanticipated and anticipated innovations to risk as well as the law of motion of risk. Source: CMR.

Parameter	Value	Description
$\sigma_{\sigma,n}$	0.0282985295279650	Standard deviation of the anticipated risk shock
$\sigma_{\sigma,0}$	0.0700061676650730	Standard deviation of the unanticipated risk shock
$\rho_{\sigma,n}$	0.3861343781103740	Correlation among signals of the risk shock
ρ_{σ}	0.9706370265612010	Autocorrelation coefficient of risk shocks

first signal is

$$\log(\xi_8) = \rho_{\sigma,n}^{8-8}\sigma_{\sigma,n}e_{\xi_8} = \sigma_{\sigma,n}e_{\xi_8}$$

To see that the strength of the signal increases over time, seven periods ahead signal is

$$\log(\xi_7) = \rho_{\sigma,n}^{8-7}\sigma_{\sigma,n}e_{\xi_8} + \sqrt{1-\rho_{\sigma,n}^2}\sigma_{\sigma,n}\rho_{\sigma,n}^{7-7}e_{\xi_7}$$

and so on. Finally, one period before of the actual change in risk, the signal is

$$\log(\xi_1) = \rho_{\sigma,n}^{8-1}\sigma_{\sigma,n}e_{\xi_8}+\sqrt{1-\rho_{\sigma,n}^2}\sigma_{\sigma,n}\rho_{\sigma,n}^{7-1}e_{\xi_7}+\sqrt{1-\rho_{\sigma,n}^2}\sigma_{\sigma,n}\rho_{\sigma,n}^{6-1}e_{\xi 6}+...+\sqrt{1-\rho_{\sigma,n}^2}\sigma_{\sigma,n}\rho_{\sigma,n}^{1-1}e_{\xi_1}$$

while the innovation to risk is

$$\log(\xi_0) = \rho_{\sigma,n}^{p}\sigma_{\sigma,0}e_{\xi_p} + \sum_{j\in\mathbb{N},p>j\geqslant 0}^{p-1}\sqrt{1-\rho_{\sigma,n}^2}\sigma_{\sigma,0}\rho_{\sigma,n}^{j}e_{\xi_j} + \sqrt{1-\rho_{\sigma,n}^2}\sigma_{\sigma,0}e_{\sigma} \text{ for } i=0. \tag{5}$$

$\sigma_{\sigma,0}$ is the standard deviation of the *un*anticipated risk shock. Without signals on the risk shocks, $\log(\xi_8) = .. = \log(\xi_1) = \rho_{\sigma,n} = 0$ and (5) simplifies to

$$\log(\xi_0) = \rho_{\sigma,n}^{p}\sigma_{\sigma,0}e_{\xi_p} + \sum_{j\in\mathbb{N},p>j\geqslant 0}^{p-1}\sqrt{1-\rho_{\sigma,n}^2}\sigma_{\sigma,0}\rho_{\sigma,n}^{j}e_{\xi_j} + \sqrt{1-\rho_{\sigma,n}^2}\sigma_{\sigma,0}e_{\sigma} = \sigma_{\sigma,0}e_{\sigma}. \tag{6}$$

To compute the magnitude of the innovations to risk, we calibrate the model using the parameters from CMR: Table 1 shows the parameter values.

Table 2 shows the magnitude of the signals and innovation used by CMR along with innovation

Table 2: Innovations to risk in different studies

	Unanticipated Shocks		Un- & anticipated Shocks
	DLS	CMR	CMR
$\log(\xi_0)$	1%	7%	10.52%
$\log(\xi_1)$	-	-	4.25%
$\log(\xi_2)$	-	-	4.25%
$\log(\xi_3)$	-	-	4.24%
$\log(\xi_4)$	-	-	4.22%
$\log(\xi_5)$	-	-	4.17%
$\log(\xi_6)$	-	-	4.04%
$\log(\xi_7)$	-	-	3.70%
$\log(\xi_8)$	-	-	2.83%

Note: The second column shows the innovation used by DLS. The third column display the innovations to risk if there are no signals. The fourth column shows risk *news* shocks, i.e. risk shocks that contain an unanticipated and an anticipated component, as introduced by CMR.

used by DLS. The second column of Table 2 shows the unanticipated innovation to risk in DLS, which is 1%. The third column shows the magnitude of the innovation to risk if there are no signals, i.e. the innovation is calculated using (6). The fourth column shows the magnitude of the innovations if there are signals to risk shocks. We compute these values using (4) and (5).

As can be seen in Table 2, there are considerable differences regarding the sequence of signals and the innovation. Compared to DLS and others, who examine the impact of risk in models with financial frictions, risk *news* shocks (the fourth column in Table 2) are larger in magnitude and with a sequence of shocks. We now turn to our quantitative analysis of effects of these different definitions of risk shocks in the framework of DLS.

2.2 Framework and Results

To examine the quantitative role of risk, DLS compare a 1% unanticipated innovation to risk with a 1% unanticipated innovation to total factor productivity (TFP). We take a similar approach in this note by comparing risk and TFP shocks in terms of the explained variation in business cycle variables. Table 3 shows the variance decomposition of the model of DLS with the three different innovations to risk displayed in Table 2. We compute the explained variation in output, consumption, investment and the bankruptcy rate following (i) a 1% unanticipated innovation in

Table 3: Variance decomposition using the framework of DLS following (i) a 1% unanticipated innovation in risk, (ii) a 7% unanticipated innovation in risk and (iii) the combination of both un- and anticipated innovations to risk.

	1% Unanticipated Shock		7% Unanticipated Shock		Un- & anticipated Shock	
	TFP	Risk	TFP	Risk	TFP	Risk
Output	99.3	0.7	74.20	25.80	46.06	53.94
Consumption	99.09	0.91	69.06	30.94	39.2	60.8
Investment	97.75	2.25	47.03	52.97	18.94	81.06
Bankruptcy Rate	38.79	61.21	4.36	95.64	1.33	98.67
Risk	100	0	0	100	0	100
TFP	0	100	100	0	100	0

Note: The process of risk is calibrated using the estimation results of CMR, see Table 1. We assume TFP follows an AR(1) process with an autocorrelation coefficient of 0.95. The innovation to TFP is 1\% for (i), (ii) and (iii).

risk, (ii) a 7% unanticipated innovation in risk and (iii) the combination of both un- and anticipated innovations to risk. As in DLS results, a 1% innovation to risk explains almost none of the variation in output, consumption and investment and 61% of the bankruptcy rate, while a 7% unanticipated innovation to risk accounts for about one quarter of the variation in output, about one third of the variation in consumption and about half of the variation in investment. Feeding back CMRs risk shocks into the model of DLS further increases the variation due to risk shocks. Risk *news* shocks account for 53.95% of output, 60% of consumption and 81% of investment. For output and consumption, the variation due to uncertainty shocks is about twice as large compared with a 7% innovation and more than sixty times larger compared to a 1% innovation. This empirical exercise suggests that the *news* component is a likely explanation for the importance of risk shocks in model of CMR, rather than the New Keynesian financial accelerator model of CMR.

2.3 Equilibrium Characteristics

To further strength our arguments, Table 4 presents the equilibrium characteristics of the model, which contains the business cycle summary statistics after simulating the model for 10,000 periods and discarding the initial 500 periods. The second column of Table 4 contains the standard deviation of risk using the different approaches to modeling risk shocks. Because there is no

Table 4: Business cycle statistics following (i) a 1% unanticipated innovation in risk, (ii) a 7% unanticipated innovation in risk and (iii) the combination of both un- and anticipated innovations to risk.

			Volatility relative to $\sigma(y)$		Correlation with y	
Shock	$\sigma(\sigma_\omega)$	$\sigma(y)$	Consumption	Investment	Consumption	Investment
1% TFP	0	0.0296	0.5068	0.5845	0.86	0.91
1% $Risk$	0.0105	0.0025	0.5600	1.040	0.28	0.90
7% $Risk$	0.0683	0.0160	0.5812	1.044	0.28	0.90
Un- & anticipated Risk	0.1414	0.0304	0.5889	1.135	0.28	0.89
U.S. Data	-	2.04	0.47	4.03	0.78	0.87

Note: The innovation in TFP is also 1% and highly persistent with an autocorrelation coefficient of 0.95. We use Dynare to simulate the model for 10,000 periods and discard the initial 500 periods. The U.S. Figures are from Dorofeenko, Lee, Salyer and Strobel (2016).

movement in risk following a TFP shock, the standard deviation of risk is zero. The standard deviation of risk using unanticipated components only is, by construction, about 1.05% and 6.83%. Finally, if the innovations contain a news component as in CMR, the standard deviation of risk is about 14 times that of DLS: 14.14% vs 1.05%. The third column displays the standard deviation of consumption and investment relative to the standard deviation of output. The fourth column shows the contemporaneous correlations with output. Regardless of the type of shocks, neither the relative volatility - nor the correlation of consumption and investment to output can match the U.S. Data. Consequently, we see these equilibrium results as further evidence that an increase in the magnitude of innovation to risk shock can indeed lead to a large component in the variance decomposition, but the increase cannot match the data.

3 Conclusion

The novel approach of CMR is that they are the first to introduce a *news* component to risk shocks. CMR (p. 49) find that "... over 60 percent of the business cycle variance in output is accounted for by the risk shock. Indeed, the risk shock is by far more important for GDP than are any of the other shocks." In this note, we show that the importance of time-varying uncertainty (i.e. risk shocks) shocks depends critically on the magnitude of the innovation and on the presence of a *news* component. Risk *news* shocks with a sequence of signals preceding the actual change in risk, is a likely explanation for accounting the different findings between CMR and others. Moreover, we find that feeding the *news* component back into the model of DLS hardly improves the business cycle statistics in terms of the volatility of consumption and investment relative to output or correlation of consumption and investment with output.

Moreover, CMR (p.49) also state that "Interestingly, with one exception the risk shock affects the economy primarily via its unanticipated component. The unanticipated component of risk is more than twice as important as the anticipated component, for GDP. It is four times as important in the case of consumption". Inspection of Table 5 and its caption in CMR, however, shows that it is the other way round - the anticipated component is four times as important for consumption and twice as important for GDP. This misinterpretation might explain why other studies, such as DLS, Bachmann and Bayer (2013), Chugh (2016) or Dmitriev and Hoddenbagh (2014) find a rather small quantitative impact of unanticipated risk shocks.

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