News and why it is not shocking: the role of micro-foundations[*]

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Abstract

A number of studies have found that news shocks account for a large part of the aggregate fluctuations of the main macroeconomic variables. We show that when taking rational expectations into consideration there is a limit on the size of the variance of the news shocks, which has not been considered in the literature. We offer an explanation to why this restriction should be imposed and show, with an empirical example from a recent paper, that if you do impose the rational expectations restriction the importance of news is drastically reduced.

Keywords: News shocks; DSGE; Rational Expectations
JEL Classification: E2; E3

1   Introduction

There is now a large body of work in macroeconomics, indeed almost a consensus, arguing that 'news shocks' contribute a high proportion of business cycle variability.

A news shock is an event occurring today that tells people about something that will happen tomorrow. A popular example was the totally credible announcement by a central bank of a future monetary policy shock, such as a cut in interest rates: also known as 'forward guidance' on future interest rate movements.

If the announcement is not totally credible then the event of the announcement becomes merely a 'signal' of a possible future cut in interest rates. Again this is an old idea, from which the work on signal extraction developed. In this case, past evidence on the connection between the announcement event and the future interest rate movement is gathered to find the best average relationship, the 'signal extraction formula'. From this, one can also recover the variance of the future movement conditional on the event and so the chances of the predicted future movement being wrong. In this example where credibility is less than full, the news shock is the belief about the future movement triggered by the announcement and the error is the difference between this belief and the actual future movement.

So why are we adding yet another paper to this large literature? For two reasons that we believe give new insight into the issue.

First, while many recognise that news shocks involve signal extraction by current agents, we think that a key element of this signal extraction channel has been overlooked hitherto; and that it provides a vital identifying condition.

Second, we have estimated the quantitative role of news shocks in a full DSGE model of the US economy subject to this condition, using a method, indirect inference, that in small samples such as we have gives low estimation bias and high test power

against inaccuracy and misspecification. We find that, according to these estimates, and contrary to most previous work, that news shocks play only a small, rather trivial, part in explaining the business cycle. In what follows we explain our approach in more detail and relate it to the eaxisting literature.

If the future movement is u_{t+1}, today's belief is u_{t+1}^e and the error is ϵ_{t+1} then we could write down the identity $u_{t+1} = u_{t+1}^e + \epsilon_{t+1}$, which is of course an identity because $\epsilon_{t+1} = u_{t+1} - u_{t+1}^e$. We can then solve our model for the effect of each variable, u_{t+1}^e and ϵ_{t+1}, respectively the news shock and the shock of the unpredicted future movement when it occurs. Notice that from the signal extraction formula based on past data together with that past data we can work out the variances of all of u_{t+1}, u_{t+1}^e and ϵ_{t+1}.

In the application of modern DSGE models with many shocks, this idea of the news shocks has been extended to many of the model's shocks. Financial shocks can be predicted from current financial developments, such as the failure of sub-prime mortgages. Productivity shocks can be forecast from current technological discoveries, such as powerful battery innovation predicting the future electric car. Investment shocks can be seen coming from current developments of robotics. The potential cases are legion. Naturally therefore economists have paid a lot of attention in recent papers to such news shocks. In this large literature, which we review below, various approaches have been made to estimating u_{t+1}^e and so ϵ_{t+1}, from macro data (the data on the signals is generally not used and often is not available to econometricians). Many authors mention that this is connected with signal extraction (e.g. recently most notably Lorenzoni (2009) and the related Blanchard et al., 2013.). However, it is important in application that the structure of restrictions between the signals and the originating shocks is fully imposed in the estimation. Lorenzoni does not apply the restriction we posit here, and nor does the paper he coauthors (Blanchard et al,

2013) in which empirical results are estimated; we discuss why below. In our paper here we show the data can be used to reveal the accuracy of the signal and hence the news shock relative to its originating fundamental shock — through a relationship we call the 'signal extraction restriction'; and we show how when this is done one can recover the effect of both fundamentals and their corresponding news shocks. We apply this to recent postwar US data and show that within a well-fitting macro model of a type widely used in recent work this restriction provides crucial identification that resolves recent concerns about news shock models raised in recent contributions by Sims (2017) and Chahrour and Jurado (2019).

Our point is simply this: u^e_{t+1} must be estimated subject to this 'signal extraction restriction', which provides a key restriction in estimation that identifies the size of the news shock. If it is not imposed and the news shock is freely estimated on the data, then its variance can become extremely large, even greater than that of the future movement itself, u_{t+1}, and it can then appear to produce very large business cycle fluctuations. For example, one could obtain very large imagined future events in one direction which then turn out not merely to occur in the direction predicted but actually to occur in the opposite direction. This is plainly a recipe for massive business cycle fluctuations first in one direction, then in the other. Some authors have found that such effects can account for most of business cycle variation, totally dominating the effects that would be produced by the original shocks themselves if not predicted at all by news shocks.

There are a variety of claims about such effects in this literature. However, the point of this paper is to show that these claims cannot be correct when the signal extraction restriction is imposed. We go on to illustrate our point comprehensively by estimating a widely-used macro model of the US through full systems indirect inference estimation, and showing how one can indeed 'find' large news shocks when

the restriction is not imposed; but that these disappear from the estimates when it is rigorously imposed, in addition to the general rational expectations restrictions always imposed in such estimation.

To understand why this is, one simply needs to think about two polar cases of news shock accuracy. First, suppose that the news shock is totally accurate, like the credible announcement of a future interest rate cut. In this case $u_{t+1} = u^e_{t+1}$ and ϵ_{t+1} is zero. We know in this case that the future interest rate cut effect is partly brought forward in time; essentially its effect is now spread across the present and the future. Its total effect on the variance of the economy is not much different from when there is no announcement or news shock. Plainly too the variance of u^e_{t+1} must be exactly equal to that of u_{t+1}; it cannot be freely estimated as it is plainly the same variable.

Second, consider the case where the news signal contains no information at all (the announcement is totally incredible). Plainly in this case $u_{t+1} = \epsilon_{t+1}$ and $u^e_{t+1} = 0$. Here we are simply back with the original model with no news.

The usual case lies somewhere in between, where there is some, but not perfect, information content in the signal. Hence there is some relationship between the future shock and the signal, therefore also with the news shock. In this case the effects of the news shock are found by simulating a proportion of the future shock brought forward in time, and another proportion occurring in the usual way when the future shock actually happens. These simulated effects on business cycle variation will lie somewhere between the effects of the two polar cases, that is somewhere between not much different from the no-news case and not at all different from it.

In the rest of this paper we develop this argument formally and illustrate its consequences by simulating a news shock about productivity within a well-known Dynamic Stochastic General Equilibrium (DSGE) model both under the signal extraction restrictions when imposed on the shocks and under different assumptions when they are

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ignored. We show that even though there are in fact rather small or negligible effects on total business cyle variation from news shocks when the signal extraction restrictions are imposed, these effects can become very large when they are not imposed. Our conclusion is that claims that news shocks per se can introduce large business cycle variation should be treated with scepticism.

In the following section we review recent work. In section 3 we set out the private signal extraction framework and how it conditions our estimation process for news shocks. In section 4 we show our own empirical work testing the news and non-news models; our main empirical finding is that news shocks make little difference to the model, so that the models with and without news shocks are equally good at matching the data. In Section 5, for robustness we generalise our work to cover all possible news shocks in the model. Section 6 summarises.

2   News shocks — recent work

The idea of news about the future (news shocks) as a source of aggregate fluctuations goes back to Pigou (1927). Positive news about future productivity increases the marginal product of future capital and thus encourages more investment, and increases aggregate demand. The positive wealth effect associated with news of an increase in future productivity causes households to consume more of both goods and leisure, thus it causes a further increase in aggregate demand and a decrease in output supply. Therefore the final effect on output is ambiguous and dependent on the magnitudes of changes in aggregate demand and supply. Business cycles can happen in the absence of large changes in fundamentals. Cochrane (1994) revived the idea and found that contemporaneous shocks to technology, money, credit and oil prices could not account for the majority of observed aggregate fluctuations. He showed

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that Vector Auto Regressions (VARs) estimated using artificial shocks to technology produce responses to consumption shocks that are similar to the corresponding responses given by VARs estimated on actual US data.

Most of the literature focuses on productivity news shocks, as do we in the main, expository, part of this paper. Much of this literature on news shocks is empirical and makes use of Structural Vector Auto Regression (SVAR) techniques to recover the news shocks. Beaudry and Portier (2006) find that news shocks are the main driver of business cycles. The largest part of Total Factor Productivity (TFP) growth is anticipated by the private sector, and thus business cycles are caused by expectation of future TFP changes. Jaimovich and Rebelo (2009) also find an important role of news about future TFP in explaining business cycles. They conclude that recessions are caused not by contemporaneous negative shocks but rather by dull news about future TFP or investment-specific technical change. Barsky and Sims (2011) propose another structural VAR approach to identify news shocks about future productivity and find that while news shocks are important in explaining output variation in the medium term, they are not a major source of post-war US recessions and so are not important drivers of business cycles.

A strand in this VAR literature has been concerned with possible non-invertibility (aka 'non-fundamentalness') of the VAR — e.g. Forni et al. (2014, 2017). This is of particular concern for VAR identification. However, the conditions for non-invertibility are demanding and in practice not much evidence of non-invertibility has been found in the relevant VARs (Sims, 2012; Fernandez-Villaverde et al, 2007; Le et al, 2016c). Under our proposed identifying restriction, there must be invertibility because future shocks can only be forecast from current news shocks; the errors containing these can be backed out from the DSGE model's equations. The DSGE model we use thus has a standard (invertible) VAR solution, which is used in our

indirect inference estimation and testing procedure.

Moving beyond the VAR technique, many recent papers use estimated DSGE models with maximum likelihood or Bayesian methods to examine the importance of news shocks in creating business cycles. The main advantage of this method over that of the familiar VAR analysis is the ability to identify simultaneously multiple sources of anticipated shocks and multi-period anticipated shocks. Fujiwara, Hirose and Shintani (2011) use Bayesian methods to estimate a model of news shocks on TFP in a New Keynesian model and find that TFP explains around 30% of output fluctuations in the US, with the contribution of the news shocks in TFP often larger than that of the unexpected component. In contrast Khan and Tsoukalas (2012), also using Bayesian methods, estimate a DSGE model and find that unanticipated shocks dominate news shocks in explaining the variation in main macroeconomic variables for the post-war period in the US. Schmitt-Grobe and Uribe (2012) find that news shocks to productivity explain a small (3%) part of the variance of the growth rates of macroeconomic variables, while other news shocks (most notably a news shock to the wage-markup which explains 17%) contribute a large part. Den Haan and Kaltenbrunner (2009) show in a search-and-matching model that unemployment too responds to news shocks, while Pavlov et al. (2013) apply them within a standard single-agent Real Business Cycle model.

However, Gortz and Tsoukalas (2017) argue that the disagreement in the literature about the importance of TFP news shocks comes about because the DSGE models in these studies do not incorporate a financial sector, and so miss out the credit channel. To remedy this, they adopt a two-sector New Keynesian model with a financial channel featuring leverage constraints. They find that news about future TFP, the majority of which is consumption-specific TFP news, explains a large fraction of the business cycle. Kamber et al. (2017) use a small open economy model with

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financial frictions and also find that news shocks to productivity generate business cycle co-movements in the main macroeconomic variables.

One can summarise this literature in two parts: the SVAR studies which generally find a large role for news shocks in explaining business cycle fluctuations and the DSGE studies whose findings for the contribution of news shocks vary substantially. In this paper we explain analytically, with empirical support, why news shocks should matter little for business cycles.

3 The micro-foundations of private-signal extraction

In this section we show that rational expectations must imply a certain relationship between news shocks and future shocks, since news shocks are a product of the signal extraction process. We will derive this relationship and point out that it has not been obeyed in the literature.

The usual way that the literature has modelled the news elements is

$$X_t = \rho X_{t-1} + \varepsilon_t + \varepsilon_{t-h}^h$$

where $u_t = \varepsilon_t + \varepsilon_{t-h}^h$ is a shock with an unanticipated element (ε_t) and an anticipated element, the news shock, $\left(\varepsilon_{t-h}^h\right)$ which is observed h periods ago. For simplicity in this exposition, we assume that news is just one period ahead and we consider the next period future shock as

$$u_{t+1} = \varepsilon_{t+1} + \varepsilon_t^1 \tag{1}$$

When incorporating 'news about future shocks' in to a model, we are postulating

that there is a direct link to the future that comes from a current public shock that is observed by agents but is not directly observed by the econometrician[1]. If this is the case, then agents will observe this news and act upon it. This action will have some effects in some of the equations of the model where they will enter as observable error terms, to be estimated by the econometrician. In the following exposition we will assume, as our example of what is going on, that the news is about future productivity, that it comes from current R&D spending, and that its effects will show up in the investment equation. Our analysis can be applied to any other source of news about the future but productivity shocks are a natural candidate for pre-cognition since their origin often lies in prior innovatory activity (in the laboratory etc). When there is news, agents can either exactly know the future (through their R&D programmes, RD) or know it with some random error. This comes about through 'signal extraction' where agents have a current noisy process from which they extract the signal they wish to identify[2]: it can be assumed that agents can obtain a statistical relationship from R&D to the latter effects by observing previous R&D programmes in the firm, and the consequences of these.

Suppose that the noisy signal, here R&D spending, consists of two elements, the varying experimental spending that directly produces future productivity, u_{t+1} (with a normalised coefficient of unity), and other unrelated experimental spending, v_{it}: thus $RD_t = u_{t+1} + v_{it}$, illustrated in the Figure 1 below.

Therefore, we have first a regression relationship of u_{t+1} on RD_t by the agents

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[1]This is not to say that they necessarily cannot be observed by econometricians. It might be possible to gather data on such things as monetary announcements, technology developments or financial events. However, in the work discussed here this is not generally done. Instead the news shocks are estimated from the macroeconomic data alone.

[2]These micro-foundations and how they affect rational expectations models have been well-known for some time: see for example Minford and Peel, 2002, chapter 3, for the workings of signal extraction and see ibid, chapter 2, pp. 65-69, for how a perfectly forecast future shock is solved for in the model.

Figure 1: Noisy Signal

carrying out signal extraction[3]:

$$u_{t+1} = \gamma RD_t + \varepsilon_{t+1} \tag{2}$$

Given the agents' failure to have complete future information, their rational expectation of u_{t+1}, $E_t u_{t+1}$, is

$$E_t u_{t+1} = \gamma RD_t \tag{3}$$

This would be what agents predict will be the outcome for u_{t+1} given their observation of RD_t; this will be the 'news shock'.

However, the econometricians modelling this news shock do not observe RD_t and simply observe current and past values of the productivity shock u. But they know

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[3] We assume these relationships are estimated by OLS because these agents do not have access to a structural model with more than this bivariate relationship

that a) agents creating the news shock do observe RD_t and b) RD_t consists of the two elements as above, $RD_t = u_{t+1} + v_{it}$ and c) these agents have an optimal signal extraction regression as above from which they derive $E_t u_{t+1}$.

These econometricians can argue as follows.

They know that agents using the signal-extraction regression will have found a coefficient of u_{t+1} on RD_t of $\gamma = \frac{cov(RD,u)}{var(RD)}$. They know also that the relationship in the opposite direction, of RD_t on u_{t+1} is $\frac{cov(RD,u)}{var(u)} = \gamma \frac{var(RD)}{var(u)}$ and the regression error is w_t so that $RD_t = \gamma \frac{var(RD)}{var(u)} u_{t+1} + w_t$. This equation could be estimated by agents who knew the R&D data; but of course it is of no use to them so they will not bother with it. Nevertheless it exists in the data.

It follows that the econometricians know that there is a relationship between the news shock and future productivity of the form $\varepsilon_t^1 = \phi u_{t+1} + \epsilon_t$. This is because the two regression relationships between productivity and R&D, yield a relationship between what agents expect and the future productivity that will occur. The econometricians do not know either of these relationships individually since they do not have access to the R&D data but they do know how they are derived. From this they can derive the relationship they need between the news shock and future productivity, as follows:

$$\varepsilon_t^1 = E_t u_{t+1} = \gamma RD_t = \gamma^2 \frac{var(RD)}{var(u)} u_{t+1} + \gamma w_t = \phi u_{t+1} + \epsilon_t$$

so that

$$\phi = \gamma^2 \frac{var(RD)}{var(u)} \text{ and } \epsilon_t = \gamma w_t$$

This tells us that the news shock, like R&D, is partly connected to future productivity (by ϕ) and partly unrelated to it (by ϵ_t). Also that $\phi = \{\frac{cov(RD,u)}{var(RD)}\}^2 \frac{var(RD)}{var(u)} = \frac{cov(RD,u)^2}{var(RD)var(u)}$ is simply the correlation coefficient between R&D and future produc-

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tivity. In what follows we will refer to ϕ for simplicity as 'the signal extraction parameter', since it is the parameter derived from the signal extraction process that we can estimate from our models, as we will see in practice below.

Of course our econometricians cannot directly estimate either ϕ or γ from data on u or RD which they do not have. However, they can work out the size of the variances of these two elements, conditional on ϕ. Thus, assuming they know something about the usefulness of the R&D signal, as measured by ϕ, they can apply this to working out the variances they must assume for the unknown stochastic variables, ε_t^1 and ϵ_t that are both key elements in the model dynamics. They can use this to estimate ϕ indirectly, by indirect inference, as we will explain below.

The explained variance of RD is $\gamma^2 (\frac{var(RD)}{var(u)})^2 var(u) = \gamma^2 (\frac{var(RD)}{var(u)}) var(RD)$. The unexplained variance of RD, $var(w)$, is

$$
\begin{aligned}
var(w) &= (1 - \gamma^2 (\frac{var(RD)}{var(u)})) var(RD) \\
&= (1 - \phi)(\frac{var(RD)}{var(u)}) var(u) \tag{4}
\end{aligned}
$$

and hence the variance of the unexplained part of $\varepsilon_t^1, \epsilon$, is

$$
\begin{aligned}
var(\epsilon) &= var(\gamma w) = \gamma^2 var(w) \\
&= \gamma^2 (\frac{var(RD)}{var(u)})(1 - \phi) var(u) \\
&= \phi(1 - \phi) var(u) \tag{5}
\end{aligned}
$$

It follows that the variance of the news shock, ε_t^1,

$$
var(\varepsilon_t^1) = \phi^2 var(u) + \phi(1 - \phi) var(u) = \phi var(u) \tag{6}
$$

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This is saying that when $\phi = 0$ the news shock has no variance because there is no news; when $\phi = 1$ the news shock is simply equal to u_{t+1} and it has no additional variance due to ϵ. Under rational expectations this restriction on the variance of the news shock ε_t^1 needs to be enforced. In general where ϕ lies between 0 and 1, $\varepsilon_t^1 = \phi u_{t+1} + \epsilon_t$, the news shock, has the part ϕu_{t+1} that is related systematically to the future event and the part that is unrelated to it, ϵ_t, which is a random draw. The point of this derivation is that the distribution from which this is a random draw, ϵ, is tightly circumscribed, with its variance related to the variance of the future shock and the signal extraction parameter, ϕ. It is this restriction that has not been respected in this news shock branch of rational expectations modelling.

This is in contrast to Lorenzoni (2009) who sets out a general approach to signal extraction and imperfect information in which agents on islands speculate about what others forecast. In this model there is no closed form expectations solution because of a many-level expectations structure as in Keynes' beauty contest. In our approach the information structure is simpler. Agents perceive past outcomes as well as past signals, and react, creating publicly observable errors in economic behaviour. All have access to this public information. Under the rational expectations hypothesis they assume all others, with the same access, form the same expectations as they do, so cutting out multi-level expectations issues, as is standard in rational expectations models' treatment of public information. It is this combination of rational expectations, public information and signal extraction that supplies us with the identifying restriction we use. Since Blanchard, L'Huillier and Lorenzoni (2013) do not use this restriction in their ML and Bayesian estimation methods, their results allow noise errors to be estimated free of it; as we show below, such estimation creates potentially very high noise in news shocks.

We now go on in the next section to explore how this restriction should be applied

to a DSGE macro model of the US widely used to evaluate news shocks and we contrast our findings with others who have not applied it.

4   Testing rational expectations models with and without news shocks

The model we use in this section is a particular model of the US economy that we have found to be empirically satisfactory — Le et al. (2016a). The model is a modified version of the familiar Smets and Wouters (2007) model of the US to which we have added flexible goods and labour sectors, a financial sector following Bernanke et al. (1999) and a money market where money is a cheap form of collateral and thus allows monetary policy still to be effective under the zero lower bound situation. The model was tested and estimated by indirect inference with nonstationary data and it has a nonstationary productivity shock. The full model listing is in Appendix 1. To incorporate productivity news shocks into the model, we assume that in the current period agents know the productivity shocks that will hit the economy in the next 8 quarters and then after that the normal non-stationary productivity process kicks in. Note that in terms of our analysis above this initially assumes that agents have perfect knowledge of future shocks, so that $\phi = 1$; we go on to discuss how the results change when we introduce imperfect signal extraction with $\phi < 1$. We use the Indirect Inference technique on this model to address the question of whether the productivity news shock contributes much to business cycles. In Section 5 we extend our treatment to further news shocks and show that our conclusion that news shocks do not contribute materially to business cycle variation is not confined to productivity.

First, we will take the model with its estimated parameters as in Le et al. (2016a)

and add the expected productivity shocks to it. We run the indirect inference test of this model (Le et al, 2016b) with expected shocks and find that the model still fits the data with the transformed Wald statistics of 1.3266^4. Without further reestimation we find that there are some differences in the model's behaviour as shown in Figure 2 for some bootstrap samples of output, investment and consumption (the blue lines are withough news). This means that when they know the future productivity shocks agents' investment and spending behave differently from when they do not know the future. However, these differences are small, as is clear from the illustrative graphs and they do not increase significantly the contribution of productivity shocks in explaining the output variation (see Table 1).
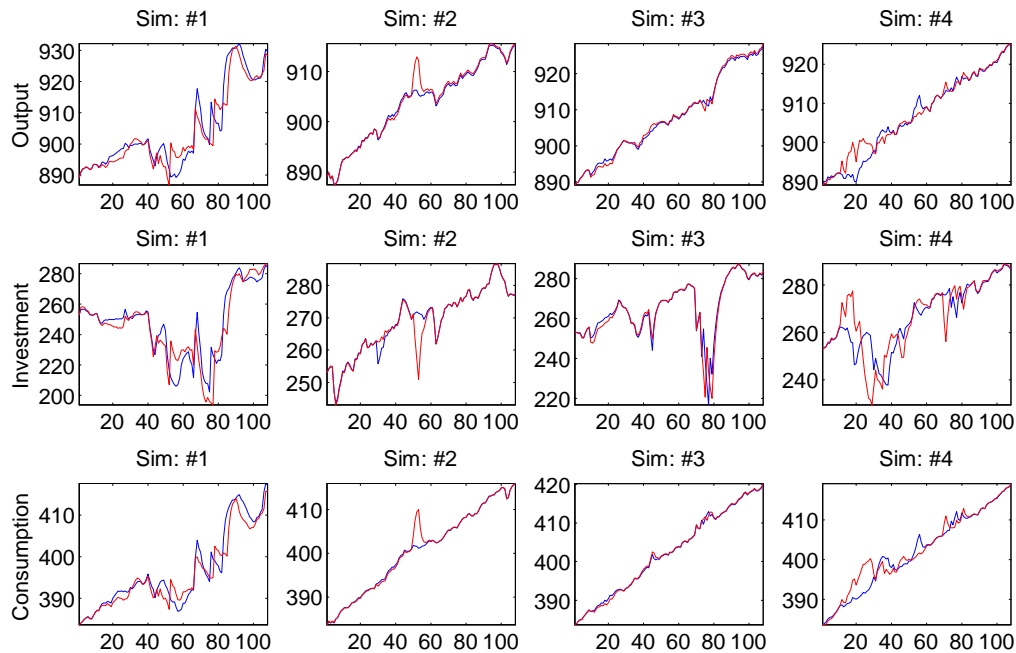

Figure 2: Comparison of Simulations with and without News

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[4]A value less than 1.645 shows the model is not rejected.

Variance decomposition	Model as estimated with and without news shocks	
Shocks	Output no news	Output with news $\phi = 1$
Govt Spending	5.73	5.72
Consumer Preference	3.69	3.68
Investment	3.30	3.29
to Interest rate	4.05	4.04
Productivity	14.52	14.76
Price Mark-up	0.64	0.64
Wage Mark-up	0.01	0.01
Labour supply	19.63	19.58
to Premium	36.55	36.45
to Networth	11.66	11.63
Money supply	0.20	0.20
Total	100	100

Table 1: Variation Decomposition for output explained by different shocks, using the coefficients of the estimated model without news shock

We will assess the marginal contribution of news shocks to the variances of endogenous variables by simulating the shocks to exogenous variables under a full range of assumptions about ϕ, which summarises how well agents can forecast the future fundamental shocks; these assumptions will identify how the shocks are divided into 'pure news' (or 'noise') and 'forecast fundamentals' — concerns of Sims (2016) and Chahrour and Jurado (2018). Our method deals with Sims' concern that the contribution of pure news may be mis-measured, because we can precisely identify its contribution. Chahrour and Jurado show that in the typical model estimation set-up there is no way to identify the role of noise; however, it is precisely such identification that our suggested explicit incorporation of the signal extraction process brings to bear on the set-up.

The identifying element is ϕ, the signal extraction parameter, which we will estimate. Our default 'news shock model' assumes $\phi = 1$, the case of perfect foresight. To begin with, we discuss the results for variances and model data-match when this set-up is substituted for the standard 'no news' model. After this, we will discuss results when foresight is imperfect so that there is noise/pure news, including the case

for the estimated ϕ.

If we allow for reestimation of the model with news shocks, we find that the new set of parameters (Table 2) is hardly any different. Since Indirect Inference is a simulations based estimation technique if the parameters have hardly changed this shows that news isn't having much effect of the simulations.

This study with a DSGE model shows that news about the future productivity shock makes only a small contribution to explaining the business cycle. This is true whether we reestimate the model or not. While we have restricted our analysis to productivity shocks, exactly the same arguments apply to other shocks; besides, productivity shocks are the most likely candidate for fore-knowledge because there is a genuine source of prior information about them from the innovatory work that precedes them. But as noted we show that the same applies when other news shocks found to be important by others, such as a financial and a wage mark-up news shock, are included in the model.

4.1 Why do news shocks have such small effects in the perfect foresight model?

In this section we aim to explain the reason of why the effects of the productivity news shock is so trivial. Imagine a world in which future productivity shocks are regularly known today; compare this with a world in which only today's productivity shocks are known. In the first, each current period people are newly told a moving average of shocks for today and a number of future periods; in the second they are just told of today's shock. If the productivity process is a homoscedastic I(1) or I(0) process, the two series will not look too different — which is what we find. Thus the people who respond to these processes, namely investors, will not respond much

Models' Coefficients			
		Estimated Model *without* news	Estimated Model *with* news $\phi = 1$
Elasticity of capital adjustment	φ	8.723	8.320
Elasticity of consumption	σ_c	1.737	1.650
External habit formation	λ	0.700	0.667
Probability of not changing wages	ξ_w	0.576	0.548
Elasticity of labour supply	σ_L	3.213	3.059
Probability of not changing prices	ξ_p	0.938	0.895
Wage indexation	ι_w	0.426	0.405
Price indexation	ι_p	0.158	0.166
Elasticity of capital utilisation	ψ	0.107	0.112
Share of fixed costs in production $(+1)$	Φ	1.387	1.323
Taylor Rule response to inflation	r_p	2.500	2.375
Interest rate smoothing	ρ	0.746	0.711
Taylor Rule response to output	r_y	0.026	0.028
Taylor Rule response to change in output	$r_{\Delta y}$	0.025	0.027
Share of capital in production	α	0.185	0.176
Proportion of sticky wages	ω^w	0.532	0.557
Proportion of sticky prices	ω^r	0.101	0.096
Elasticity of the premium with respect to leverage	χ	0.034	0.032
Money response to premium	ψ_2	0.84	0.080
Elasticity of the premium to M0	ψ	0.050	0.047
Money response to credit growth	ψ_1	0.046	0.044
Transformed Wald $(Y, \pi, R)^*$		0.0239	0.1142

*A value less than 1.645 shows the model is not rejected.

Table 2: Coefficient Estimates (1984Q1-2011Q4)

differently.

Consider the following simple case. Let productivity, κ_t, be a random walk: $\kappa_t = \kappa_{t-1} + \epsilon_t$. In the simple case where people only observe the current shock, the expectations of productivity for $t+i$ that drive stock markets will be $E_t \kappa_{t+i} = \kappa_{t-1} + \epsilon_t$ $(i = 1, 2, ...)$

Now consider the case where we will assume people observe the next period shock, ϵ_{t+1}, in this period. Now

$$E_t \widetilde{\kappa}_{t+i} = \kappa_{t-1} + \epsilon_t + \epsilon_{t+1} (i = 1, 2, ...)$$

Hence $E_t \widetilde{\kappa}_{t+i} = E_t \kappa_{t+i} + \epsilon_{t+1}$. The two series only differ by the future innovation. The innovations in each series are: $E_t \kappa_{t+i} - E_{t-1} \kappa_{t+i-1} = \epsilon_t$ and $E_t \widetilde{\kappa}_{t+i} - E_{t-1} \widetilde{\kappa}_{t+i-1} = \epsilon_{t+1}$. Thus the $E_t \kappa_{t+i}$ series, assuming a zero initial value for κ_{-1}, runs from period 0: $\epsilon_0, \epsilon_0 + \epsilon_1, \epsilon_0 + \epsilon_1 + \epsilon_2, ...$ while the $E_t \widetilde{\kappa}_{t+i}$ series runs: $\epsilon_0 + \epsilon_1, \epsilon_0 + \epsilon_1 + \epsilon_2, ...$ One series is simply the lagged value of the other. That is, when one has news shocks one reacts earlier to events; however the reaction is not much different. Close inspection of the red (with news) and blue (without news) lines in the graphs of different output simulations reveals exactly this type of pattern. The red line moves before the blue line. However the random movements are not essentially different.

Another way of putting the matter is this. Suppose we simulate a model repeatedly with a unit root time-series error, w_t, whose innovation variance is V but has a randomly chosen initial value of w_0. Then we simulate it again repeatedly with the same error process, with the same variance, but with a different randomly chosen initial value, $\widetilde{w_0}$. We will observe some small differences in behaviour because of the difference in random initial value but they are likely to be small. This is what we see in this paper.

In this paper the news shock (illustrated for one period ahead) is $\varepsilon_t^1 = \phi u_{t+1} + \epsilon_t$, where in general $var(\epsilon) = \phi(1 - \phi)var(u)$. We have set $\phi = 1$ which implies that the variance of ϵ is zero. The other authors of DSGE models reviewed here all set $\phi = 1$ as we do but they additionally include ϵ_t with a finite variance, which they allow to be estimated. However, this violates rational expectations as we have shown above. If these authors wish there to be an error in expecting future TFP then they should insert a ϕ that is less than one and an accompanying error whose variance is circumscribed as above. Effectively, what they have done is like adding a sunspot to the model solution. If this is the case then it would mean more variation in this random term ϵ would lead to it having more effect in explaining the variation of macroeconomic variables. We conduct some experiments where ϵ takes different variances. This reflects the different results found for the importance of news shocks, as reported in the literature. Schmitt-Grohe and Uribe (2012) report the mean of the posterior distribution's standard deviation for the surprise TFP shocks at 0.63, and much smaller standard deviations of ϵ at four (0.17) and eight (0.21) periods ahead. Gortz and Tsoukalas (2017) use the mean posterior distribution's standard deviation for the consumption sector TFP shocks of 0.172, together with that of ϵ at 0.1174 and 0.2014 respectively for the four and eight periods ahead. Differences in the size of news shocks led to different conclusions about the role of the news in explaining the variables' movements. In our model, the standard deviation of the TFP shocks is 0.44.

Table 3 shows how the variance attributable to TFP shocks changes as one adds in the extra ϵ shock. In the 1st column we show the decomposition when people have no knowledge at all of the future TFP shock ($\phi = 0$). The 2nd column shows the situation when people have exact knowledge of the future shock, the default case where $\phi = 1$. The 3rd column shows the case when there is signal extraction and

know half the shock ($\phi = 0.5$) plus the implied random ϵ. As one can see these three columns differ only in minor ways.

Then in the following columns we keep the same signal extraction formula ($\phi = 0.5$) but add a random ϵ with unrestricted and progressively higher variance. In these we see clearly how the decomposition changes, with a steadily rising contribution of TFP shocks as this ϵ variance increases.

Assumptions for ϕ.	No News $\phi = 0$	Perfect foresight $\phi = 1$ $e_t = u_{t+1}$	With signal extract TFP shocks $\phi = 0.5$ $e_t = 0.5u_{t+1} + \epsilon_t$ $var(\epsilon) = 0.25var(u)$	With signal extract TFP shocks + random error ϵ (stdev =0.5) $\phi = 0.5$	With signal extract TFP shocks + random error ϵ (stdev =0.7) $\phi = 0.5$	With signal extract TFP shocks + random error ϵ (stdev =1.0) $\phi = 0.5$
Interest rate	43.90	44.55	17.40	27.17	29.84	35.35
Investment	5.17	5.27	4.44	16.81	20.15	25.63
Tobin's q	32.26	31.83	18.35	30.34	32.13	34.05
Capital	6.35	6.35	3.83	17.53	21.75	29.41
Inflation	45.62	45.38	16.62	30.84	34.57	40.84
Wage	26.36	26.64	13.63	42.03	49.72	60.64
Consumption	24.21	24.68	17.26	59.24	68.32	78.57
Output	**14.52**	**14.76**	**11.49**	**40.77**	**49.35**	**61.31**
Hours	23.30	23.06	9.91	30.82	37.80	48.64
Return on Capital	17.91	18.08	9.92	33.52	41.53	53.33
Premium	1.53	1.59	0.98	4.65	5.32	6.13
Networth	7.43	7.48	3.80	11.38	13.50	16.26

Table 3: Contribution of productivity shocks

What this table reveals is that the importance of the productivity news shock critically depends on the addition of a free random error which violates rational expectations. Under rational expectations restrictions news shocks appear, according to our work here, to have merely trivial effects. This can be seen clearly for output for example, shown in bold, by comparing columns 2 and 3 with column 1 which is the case with no news at all. Column 2 shows the case where future productivity growth is fully known at t; here the variance of output is trivially higher. Column 3 shows where the news shock is half correct; in this case the variance is slightly lower than the no-news case. Now consider columns 4 to 6. Here the variance of the news shock has been steadily boosted, it is assumed by estimation disregarding the restrictions from signal extraction: the variances progressively rise by potentially large amounts.

Similar patterns are observed for other variables.

Alternatively, this idea can be shown by looking at the Figure 3, where we show on the left the various output IRFs for a future $(t + 1)$ TFP shock which is a) not forecast at all; the bottom line b) perfectly forecast at time t; second from bottom. c) signal extraction $(\phi - 0.5)$ with the variance of ϵ restricted by rational expectations, the shock size is 0.36: the top line,with diamonds.

Notice that the addition of news, with perfect foresight, brings the effect fowards in time, leaving the long-run effect the same. Adding imperfect foresight with some signal extraction, slightly offsets this bringing forward but compensates later by an offsetting realisation of the truth.

On the right hand side the other lines show the IRFs for three cases of higher ϵ shock variances. As the shock variance increases the effect is brought forward in time as well as increasing the long-run effect.

Plainly therefore, allowing the ϵ shock variance to be determined without restriction allows small sample estimation to insert variances that may cause large volatility in the model. This extra degree of freedom in estimation is prevented by the rational expectations restriction however.

What we have done here therefore is to attempt to replicate, using a widely-used DSGE model of the US estimated to fit US data, the various findings about the role of news shocks in the DSGE model news literature, where a variety of DSGE models are used but all of which are estimated on US data and therefore reflect the same general US macro facts. Our point is simply this: given that all authors implicitly assume that signal extraction is occurring, there is a restriction on the variance of the error agents can make in estimating the future. If this restriction is imposed, then the role of news shocks in contributing to macro variance is rather small. However, if it is not imposed and the errors are freely estimated, then the role can become extremely
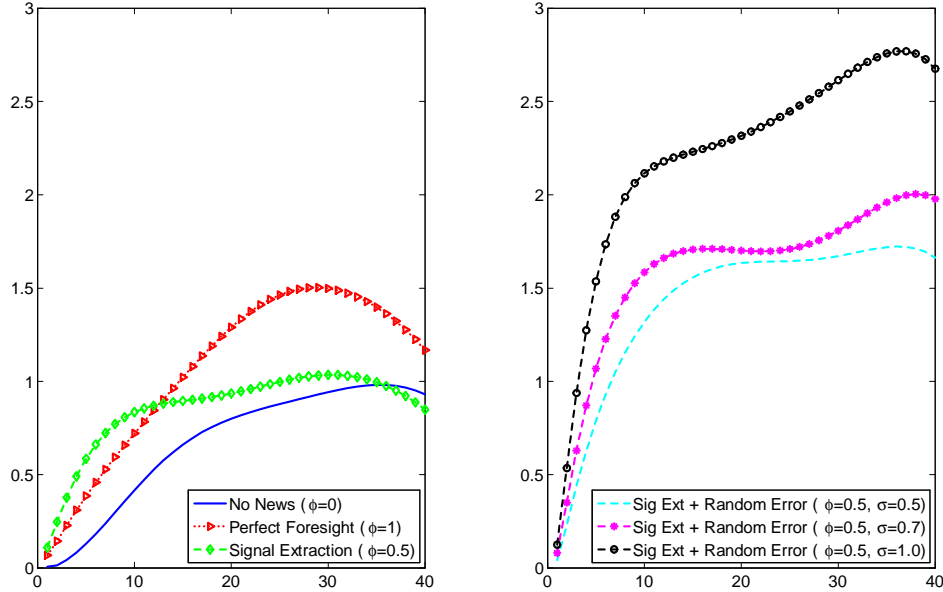
Figure 3: Output's IRFs for different shock assumptions

large. This nevertheless is invalid.

Lastly, we can exploit our restriction on the variance of the 'noise' relative to the variance of the fundamental to estimate the signal extraction parameter, ϕ. Effectively, then, our restriction enables identification of noise and fundamental, whereas without it we are in the situation described by Chahrour and Jurado (2018) that a news model with perfect foresight is observationally equivalent to one with pure noise. In Figure 4 we show the Transformed Wald for different values of ϕ. The minimum value occurs when $\phi = 0.32$, therefore this is the estimate of ϕ for the productivity shock in the model being used here.

For good measure we carry out a test of identification on the ϕ parameter, using the method in Le et al. (2017). The idea is that if the coefficient is identified then, when we use a large sample, as we move away from the true value of that
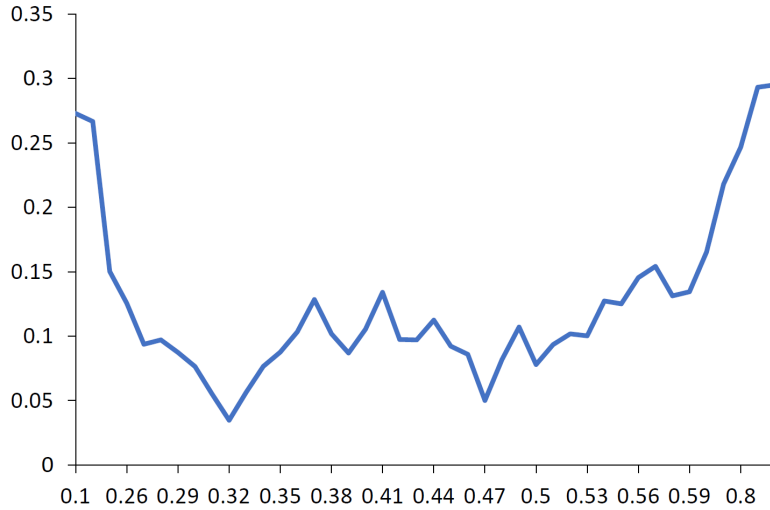
Figure 4: Transformed Wald Statistic for different values of ϕ

coefficient the model will be rejected at a higher requency than 5%, the test size. We perform the following Monte Carlo experiment. We treat the model with perfect foresight ($\phi = 1$), our 'default news model', as the 'true' model. We generate a large number of simulations with a large sample size from this model (3000 simulations with 500 observations) and use our Indirect Inference procedure to calculate a Wald statistic, using a large VAR as the auxiliary model, for each simulation. This gives a distribution of Wald statistics from the 'true'. We then alter ϕ to give us a 'false' model and generate a similarly large number of simulations. On each of these 'false' simulations we calculate the Wald statistic and see how many of them are rejected by the true model. If ϕ is not identified then as we move ϕ away from the 'true' value we should continue to reject 5% of the 'false' simulations at the 95% confidence level, implying that the test cannot distinguish the false reduced form from the true one, so that more than one structural model yields the same reduced form. However, if ϕ is identified then as we move away from the 'true' value then more of the 'false' simulations should be rejected. The results of this identification test are shown in

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Table 4. We find that, indeed, ϕ is identified as the rejection rate increases as we move away from the 'true' model. From this we can conclude that the value of ϕ can be estimated and should not be set arbitrarily.

	Values of ϕ				
					(True)
	0.1	0.2	0.6	0.8	1.0
Rejection Rate	25.7%	22.2%	11.3%	8.60%	5.00%

Table 4: Identification of ϕ parameter

5   Robustness Check

It may be argued that our analysis so far is quite restrictive, since we have only included news shocks to TFP. As a robustness check we included news in all the shocks of the model and recalculated the variance decomposition. In Tables 5 and 6 we report the full variance decomposition for all variables for the model without news, and with all news shocks respectively. We find that, again, the difference between the two are small for all variables. We also report the total variance, which again shows very little difference when including news shocks. From this we conclude that our findings in the previous section when just including news in TFP follow through to the more general case.

6   Concluding remarks

In this paper we examine the evidence concerning the role of news shocks. By this we mean that agents observe some data that is not observed by the econometrician and this allows them to forecast future (publicly known) shocks by using the past relationships between their information and the public data on these shocks, in an

	Real Interest Rate	Invest-ment	Tobin's Q	Capital	Inflation	Real Wage	Consum-ption	Output	Labour Supply	Return on Capital	Premium	Net Worth
Government Spending	0.96	0.04	0.15	0.02	0.76	3.50	0.25	5.73	4.60	3.06	0.04	0.06
Consumer Preference	0.34	0.01	0.03	0.00	0.29	4.33	6.47	3.69	1.96	3.01	0.01	0.02
Investment	1.11	4.16	1.30	6.09	0.89	2.81	3.53	3.30	2.25	3.42	0.97	0.99
Taylor Rule	4.26	0.40	2.17	0.33	1.66	4.26	3.59	4.05	2.32	3.21	0.16	0.70
Productivity	43.90	5.17	32.26	6.35	45.62	26.36	24.21	14.52	23.30	17.91	1.53	7.43
Price Mark-up	2.21	0.06	0.46	0.04	8.38	0.77	0.56	0.64	0.35	0.55	0.05	0.17
Wage Mark-up	0.00	0.00	0.00	0.00	0.00	0.14	0.00	0.01	0.01	0.06	0.00	0.00
Labour	6.56	6.29	11.22	6.69	4.70	22.52	34.66	19.63	28.96	11.61	0.49	1.83
Premium	32.05	63.14	33.60	62.89	30.47	27.89	22.71	36.55	26.59	43.36	52.64	20.30
Networth	8.59	20.59	14.86	17.06	7.22	7.29	4.01	11.66	9.53	13.71	34.83	58.86
M0	0.02	0.14	3.95	0.53	0.01	0.12	0.01	0.20	0.14	0.12	9.28	9.63
Total Variance	1.30	434.46	75.84	45.35	0.33	51.87	6.33	15.05	4.56	1.24	1.16	880.49

Table 5: Variance Decomposition without News in Every Shock

	Real Interest Rate	Invest-ment	Tobin's Q	Capital	Inflation	Real Wage	Consum-ption	Output	Labour Supply	Return on Capital	Premium	Net Worth
Government Spending	0.91	0.05	0.16	0.03	0.72	3.39	0.26	5.36	4.44	2.92	0.04	0.06
Consumer Preference	0.31	0.01	0.03	0.00	0.26	4.04	6.17	3.37	1.86	2.79	0.01	0.02
Investment	1.06	4.18	1.28	5.83	0.85	2.84	3.64	3.25	2.29	3.23	0.94	1.00
Taylor Rule	3.94	0.40	2.14	0.33	1.57	4.25	3.61	3.95	2.36	3.23	0.16	0.72
Productivity	44.88	5.28	33.51	5.97	46.04	24.89	23.61	13.51	20.94	16.84	1.77	8.56
Price Mark-up	2.05	0.06	0.46	0.04	7.65	0.75	0.55	0.62	0.35	0.54	0.05	0.17
Wage Mark-up	0.00	0.00	0.00	0.00	0.00	0.14	0.00	0.01	0.01	0.06	0.00	0.00
Labour	6.41	6.18	11.48	6.38	4.70	21.13	34.05	19.20	28.74	11.29	0.52	2.08
Premium	32.19	63.46	33.55	63.97	31.12	30.73	24.24	38.64	28.88	45.09	53.87	20.83
Networth	8.23	20.29	14.42	16.98	7.09	7.77	3.85	11.93	10.02	13.89	34.43	58.65
M0	0.02	0.11	2.99	0.48	0.01	0.09	0.01	0.15	0.11	0.13	8.21	7.90
Total Variance	1.34	436.83	73.62	43.57	0.34	51.02	6.15	15.20	4.44	1.23	1.04	787.80

Table 6: Variance Decomposition without News

optimal signal extraction procedure. By contrast, econometricians estimate the news shock by relating it both to current events and to future fundamental shocks.

Work based on DSGE models has also found only limited effects of news shocks, by contrast with work based on SVARs. DSGE modellers have interpreted this as suggesting that the SVAR identification of news shocks could be at fault. However, there are examples of DSGE models where news shocks have a large effect — two prominent examples are Schmitt-Grohe and Uribe (2012) and Gortz and Tsoukalas (2017), both of which use various estimated DSGE models of the same US data.

We investigated how this finding could have occurred by simulating a version of Smets and Wouters' (2007) widely-used DSGE model of the US from Le et al. (2016a), which passed stringent indirect inference tests, and added news shocks to it.

We found that the model with news shocks still passed the tests but was hardly altered by the addition, and that the effects of the news shocks within it were trivial when we imposed on them the restriction from the signal extraction procedure limiting the variance of mistakes in predicting future shocks, so-called 'false news'. It turns out that if the variance of false news is allowed, via free estimation, to be larger than permitted by this restriction, then indeed the role of news shocks in contributing to macro variance can become very large.

Within our model any news shocks that are correctly anticipated do not alter in any essential way the stochastic structure of the model, merely advancing the date at which the same innovations are registered by agents. However it would seem that some DSGE authors have added to that part of the news shock that is correctly anticipated a random error term representing 'false news', which depending how large its variance is estimated to be can have potentially large effects. We show in this paper that adding this error without the correct restriction on its variance violates the restrictions imposed by signal extraction under rational expectations; once this restriction is imposed the role of news shocks effectively disappears.

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7 Appendix 1: Le et al. (2016) Model Listing

Consumption Euler equation

$$c_t = \frac{\frac{\lambda}{\gamma}}{1 + \frac{\lambda}{\gamma}} c_{t-1} + \frac{1}{1 + \frac{\lambda}{\gamma}} E_t c_{t+1} + \frac{(\sigma_c - 1) \frac{W_* L_*}{C_*}}{\left(1 + \frac{\lambda}{\gamma}\right) \sigma_c} (l_t - E_t l_{t+1}) - \left(\frac{1 - \frac{\lambda}{\gamma}}{\left(1 + \frac{\lambda}{\gamma}\right) \sigma_c} \right) (r_t - E_t \pi_{t+1}) + eb_t \tag{7}$$

Investment Euler equation

$$inn_t = \frac{1}{1 + \beta \gamma^{(1-\sigma_c)}} inn_{t-1} + \frac{\beta \gamma^{(1-\sigma_c)}}{1 + \beta \gamma^{(1-\sigma_c)}} E_t inn_{t+1} + \frac{1}{(1 + \beta \gamma^{(1-\sigma_c)}) \gamma^2 \varphi} qq_t + einn_t \tag{8}$$

Tobin Q equation

$$qq_t = \frac{1 - \delta}{1 - \delta + R_*^K} E_t qq_{t+1} + \frac{R_*^K}{1 - \delta + R_*^K} E_t rk_{t+1} - E_t cy_{t+1} \tag{9}$$

Capital Accumulation equation

$$k_t = \left(\frac{1-\delta}{\gamma}\right) k_{t-1} + \left(1 - \frac{1-\delta}{\gamma}\right) inn_t + \left(1 - \frac{1-\delta}{\gamma}\right) \left(1 + \beta\gamma^{(1-\sigma_c)}\right) \gamma^2 \varphi \left(einn_t\right)$$

(10)

Price Setting equation

$$
\begin{aligned}
rk_t \;=\; & \omega^r \left[
\frac{1}{\alpha\left(\frac{1}{1+\beta\gamma^{(1-\sigma_c)}\iota_P}\right)\left(\frac{\left(1-\beta\gamma^{(1-\sigma_c)}\xi_p\right)\left(1-\xi_p\right)}{\xi_p\left((\phi_p-1)\epsilon_p+1\right)}\right)}
\left\{
\begin{array}{c}
\pi_t - \frac{\beta\gamma^{(1-\sigma_c)}\iota_P}{1+\beta\gamma^{(1-\sigma_c)}\iota_P}E_t\pi_{t+1} - \frac{\iota_P}{1+\beta\gamma^{(1-\sigma_c)}\iota_P}\pi_{t-1} + \left(\frac{1}{1+\beta\gamma^{(1-\sigma_c)}\iota_P}\right) \\
\left(\frac{\left(1-\beta\gamma^{(1-\sigma_c)}\xi_p\right)\left(1-\xi_p\right)}{\xi_p\left((\phi_p-1)\epsilon_p+1\right)}\right)\left((1-\alpha)\,w_t - ea_t\right) - ep_t
\end{array}
\right\}
\right] \\
& + (1-\omega^r)\left[\frac{ea_t}{\alpha} - \frac{1-\alpha}{\alpha}w_t\right]
\end{aligned}
$$

(11)

Wage Setting equation

$$
\begin{aligned}
w_t \;=\; & \omega^w \left[
\begin{array}{c}
\frac{\beta\gamma^{(1-\sigma_c)}}{1+\beta\gamma^{(1-\sigma_c)}}E_t w_{t+1} + \frac{1}{1+\beta\gamma^{(1-\sigma_c)}}w_{t-1} + \frac{\beta\gamma^{(1-\sigma_c)}}{1+\beta\gamma^{(1-\sigma_c)}}E_t\pi_{t+1} - \frac{1+\beta\gamma^{(1-\sigma_c)}\iota_w}{1+\beta\gamma^{(1-\sigma_c)}}\pi_t \\
+ \frac{\iota_w}{1+\beta\gamma^{(1-\sigma_c)}}\pi_{t-1} - \frac{1}{1+\beta\gamma^{(1-\sigma_c)}}\left(\frac{\left(1-\beta\gamma^{(1-\sigma_c)}\xi_w\right)\left(1-\xi_w\right)}{(1+\epsilon_w(\phi_w-1))\xi_w}\right) \\
\left(w_t - \sigma_l l_t - \left(\frac{1}{1-\frac{\lambda}{\gamma}}\right)\left(c_t - \frac{\lambda}{\gamma}c_{t-1}\right)\right) + ew_t
\end{array}
\right] + \\
& (1-\omega^w)\left[\sigma_l l_t + \left(\frac{1}{1-\frac{\lambda}{\gamma}}\right)\left(c_t - \frac{\lambda}{\gamma}c_{t-1}\right) - (\pi_t - E_{t-1}\pi_t) + ew_t^S\right]
\end{aligned}
$$

(12)

Labour demand

$$l_t = -w_t + \left(1 + \frac{1-\psi}{\psi}\right) rk_t + k_{t-1}$$

(13)

Market Clearing condition in goods market

$$y_t = \frac{C}{Y}c_t + \frac{I}{Y}inn_t + R_*^K k_y \frac{1-\psi}{\psi}rk_t + c_y^e c_t^e + eg_t \tag{14}$$

Aggregate Production equation

$$y_t = \phi\left[\alpha\frac{1-\psi}{\psi}rk_t + \alpha k_{t-1} + (1-\alpha)\,l_t + ea_t\right] \tag{15}$$

Taylor Rule

$$r_t = \rho r_{t-1} + (1-\rho)\,(r_p\pi_t + r_y y_t) + r_{\Delta y}\,(y_t - y_{t-1}) + er_t \text{ for } r_t > 0.0625 \tag{16}$$

Premium

$$E_t cy_{t+1} - (r_t - E_t\pi_{t+1}) = pm_t = \chi\,(qq_t + k_t - n_t) - \psi m_t + \xi_t + epr_t \tag{17}$$

Net worth

$$n_t = \frac{K}{N}\,(cy_t - E_{t-1}cy_t) + E_{t-1}cy_t + \theta n_{t-1} + enw_t \tag{18}$$

Entrepreneurial consumption

$$c_t^e = n_t \tag{19}$$

M0

$$\Delta m_t = \psi_1\Delta M_t + errm_{2t} \text{ for } r_t > 0.0625 \text{ and } \Delta m_t = \psi_2(s_t - c^*) + errm_{2t} \text{ for } r_t \le 0.0625 \tag{20}$$

M2

$$M_t = (1 + \nu - \mu)k_t + \mu m_t - \nu n_t \tag{21}$$

8   Appendix 2: Bootstrap samples of macro variables with and without news shocks
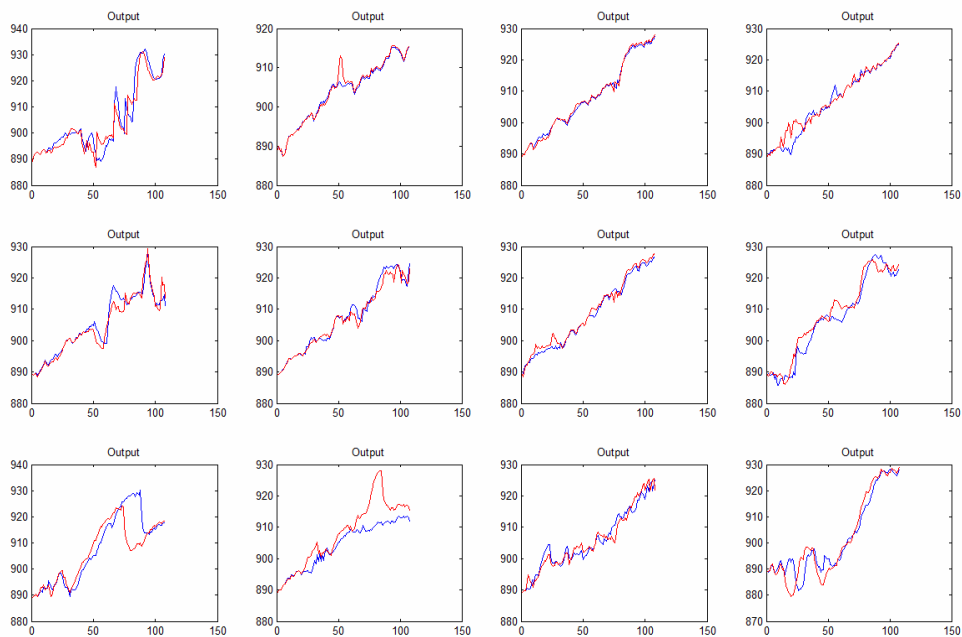

Figure 5: Different samples of output simulation (blue=no news, red=news)
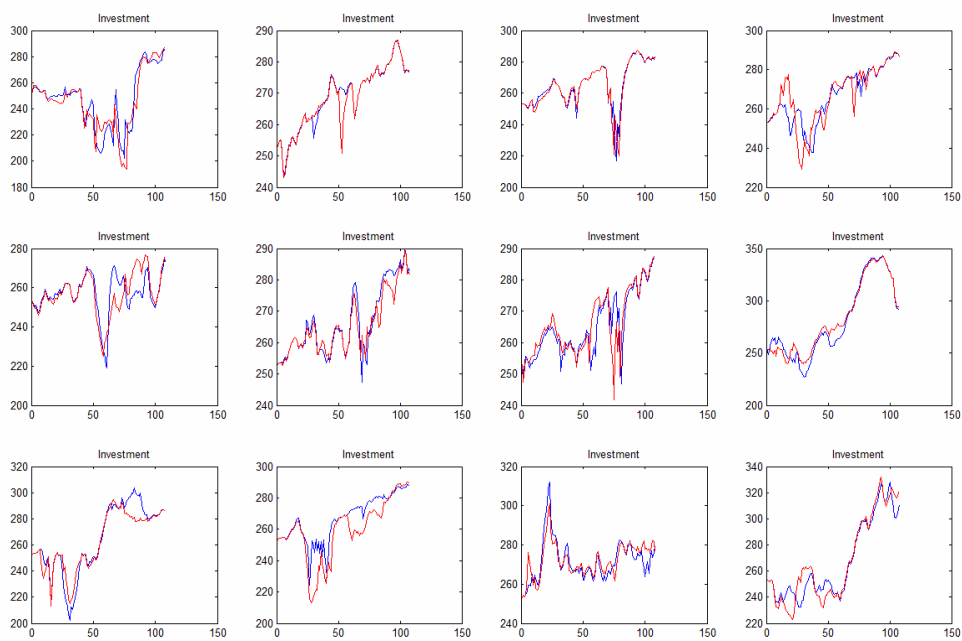
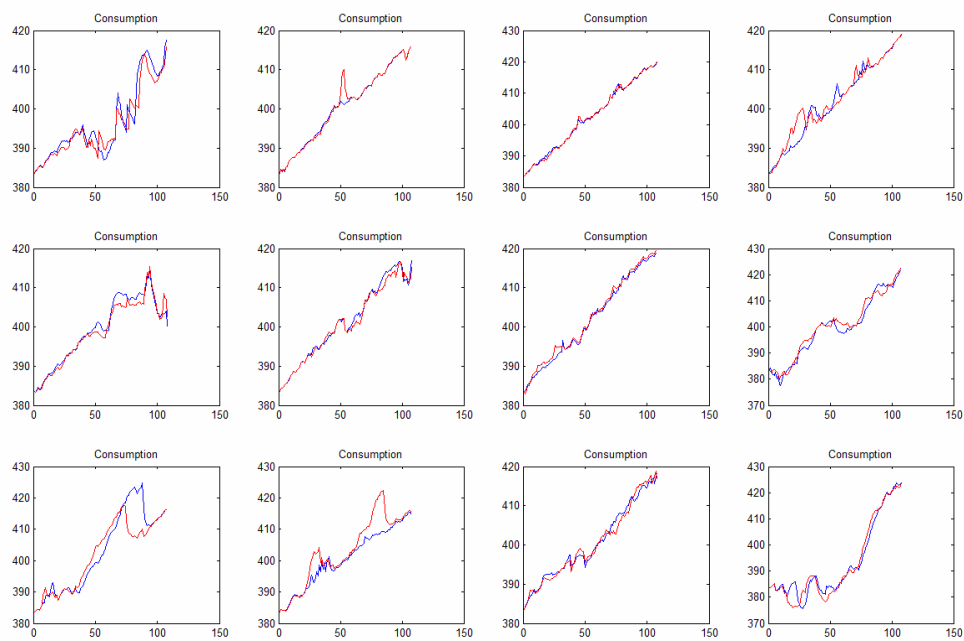Figure 6: Different samples of investment simulations (blue=no news, red=news)

Figure 7: Different samples of consumption simulation (blue=no news, red=news)