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Vo Phuong Mai Le, David Meenagh and Patrick Minford

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Cardiff Business School
Cardiff University
Colum Drive
Cardiff CF10 3EU
United Kingdom
t: +44 (0)29 2087 4000
f: +44 (0)29 2087 4419
business.cardiff.ac.uk

A note on news about the future: the impact on DSGE models and their VAR representation*

Vo Phuong Mai Le†

(Cardiff Business School, Cardiff University)

David Meenagh

(Cardiff Business School, Cardiff University)

Patrick Minford

(Cardiff Business School, Cardiff University, and CEPR)

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Abstract

In this paper we investigate the role of news shocks in aggregate fluctuations by comparing the empirical performance of models with and without the feature of the news shocks. We found a trivial difference between the two models. That is, the model with news shocks explains the variation as well as the alternative. The reason is that the news shocks can only advance the date at which agents know about the changes, but they do not change the stochastic structure of the model.

Keywords: News shocks; DSGE; VAR; Indirect Inference

JEL Classification: E2; E3

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†Corresponding author: B22, Aberconway building, Cardiff Business School, Colum Drive, Cardiff, UK, CF10 3EU. Tel.: +44 (0)29 20876566. Fax: +44 (0)29 2087 4419. (Levp@cardiff.ac.uk)

The aim of this paper is to examine whether models that contain news shocks are in an important way different from, and superior to, models that do not. There has been a substantial amount of recent work focusing on these shocks; the idea is that there is private information about future developments, for example about future productivity changes known in advance by laboratory workers, and that this information is acted upon by these people and their contacts in the form of investment and consumption plans. Hence this information about the future influences the current behaviour of the economy but plainly since the future has not yet occurred one cannot extract this shock in the usual way by inference from current and past events. In this recent work efforts have been made to identify these shocks and different assessments have been made about their importance. We discuss these efforts in detail below. We then go on to make an assessment of our own that builds on one major strand of this work using DSGE models.

Our investigation of models with different news specifications relies on the powerful method of indirect inference whereby one tests whether the VAR representation of the data can be considered to come from the model-derived VAR distribution — see Le et al (2016b). The method uses a Wald statistic where the covariance matrix is given by the model-restricted distribution (and not by the data-based distribution as in a standard Wald). This test normally assumes that the representation of the true (and also the proposed) model is a VAR. However, news shocks may cause the representation to be a VARMA where the MA component may be non-invertible, implying so-called 'non-fundamentalness'. We consider how in practice this issue plays out in the data and the models we examine.

In the next section we review this recent work on news shocks and the issues that it raises. We then set out in the following section our own empirical work testing the news and non-news models. Section 3 concludes.

1 News shock — 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 aggregate 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 suggested that consumption and output might move on news.

Much of this literature on news shocks is empirical and makes use of SVAR techniques to recover the news shocks. Beaudry and Portier (2006) find that news shocks are the main driver of business cycles. They propose two identification schemes to find the news shocks using a bivariate VAR model for total factor productivity and stock prices. They impose sequentially either impact or long run restrictions on the orthogonalized moving average representation of the data. They isolate a news shock that represents movements or innovations in stock prices, which are uncorrelated with innovations in TFP, and a disturbance that drives long-run movements in TFP. There is a positive correlation of almost unity between these two innovations, which means that positive permanent changes in productivity growth are preceded by stock market booms, and cause business cycle variations. The largest part of 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. The method is an application of principal components. News shocks are identified as the first principal component of observed TFP orthogonalized with respect to its own innovation. Thus it will be the best at explaining the variation in future TFP. They let the data dictate without much restriction what news shocks are. In discussion of the method's suitability, they perform a Monte Carlo exercise on a neoclassical model with real frictions and a news shock, and estimate the same structural VAR. The news shock is identified by maximising the variance share of technology over a ten year horizon. By comparing the IRFs, they conclude that the estimated responses to news shocks are broadly consistent with the true dynamics at all horizons. While news shocks are important in explaining the output variation in the medium term, they find they are not a major source of post-war US recessions and so are not important drivers of business cycles.

In the time series literature, Robertson and Wright (2012) have drawn our attention to 'non-fundamental' time-series processes (first highlighted by Lippi and Reichlin, 1994) in which endogenous variables are related to moving averages of shocks that cannot be recovered from the data on the endogenous variables because the MA process is not invertible. Thus, the observables are driven by future shocks; yet this raises the issue of whether this can be possible since the future is unknowable. It can be shown that DSGE models with standard stationary shocks (i.e. current and lagged shocks and no news) have a VAR solution that is fundamental in the model's structural shocks — Wickens, 2012, pp. 506-8). However, DSGE models with 'news shocks' appear to be capable of generating VARMA solutions that are nonfundamental, essentially because they introduce 'future shocks' into the models; this would appear to suggest that the future is in fact somehow knowable and so non-fundamentalness may occur. Of course this is what is asserted in news shock models — in the appendix we examine examples of DSGE models with and without this non-invertibility property.

Fernandez-Villaverde, Rubio-Ramirez, Sargent and Watson (2007) study the conditions under which DSGE models produce a moving average representation in the observables which can be inverted into a VAR representation where the VAR innovations correspond to structural shocks. However, invertibility might be a problem once news shocks are introduced in DSGE models because this creates unobservable state variables which are not in the estimated VAR. Leeper, Walker and Yang (2013) show that news about future economic fundamentals can create non-fundamental representations; this creates a gap between the VAR innovations and the structural shocks, undermining the conclusions drawn from structural VARs. On the other hand, Sims (2012) shows that the innovations of the VAR representation contain the true structural shocks and the error in forecasting the state. Non-invertibility is a problem if the innovation variance from the VAR is strictly larger than the innovation variance in the structural DSGE model, i.e. the error in forecasting the state is non-zero. Further, non-invertibility only matters quantitatively if this forecast error is big. That is, the VAR innovations may map very closely into the structural shocks despite the invertibility problem. The studies start with estimation of a finite VAR on two variables, with TFP first and output second. Imposing restrictions, the surprise movements in TFP growth are identified as the surprise technology shock, and surprise movements in output orthogonalized with respect to TFP innovations are identified as the news shock. Then Sims chooses a calibrated DSGE model that can produce the observed output and its components, in order to conduct the following Monte Carlo experiments: create 500 different data sets with 200 observations each, estimate a VAR with 8 lags and orthogonalize the innovations such that TFP growth is ordered first; for each simulation compute impulse response to news and surprise technology shocks, and compare the distribution of estimated responses to the true responses from the model. He shows that on average the SVAR captures well the qualitative dynamics of the IRFs to both kinds of news and to surprise TFP shocks.

Moving beyond the VAR technique, many recent papers use DSGE models estimated 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. Schmitt-Grohe and Uribe (2012) argue that estimation based on a formal dynamic stochastic, optimising and rational expectations model does not suffer from the invertibility problem. The full-information likelihood-based method can identify standard deviations of the surprise and anticipated components of shocks because in a theoretical model, the observable variables react differently to these types of shocks, so one can recover the anticipated shocks. They illustrate this method using the following simple model as an example:

$$
\begin{aligned}
x_t &= \rho_x x_{t-1} + \varepsilon_t^0 + \varepsilon_{t-1}^1 + \varepsilon_{t-2}^2 \\
y_t &= \rho_y y_{t-1} + \varepsilon_t^1 \\
z_t &= \varepsilon_t^2
\end{aligned}
$$

where $\varepsilon_t^i \sim N\left(0, \sigma_i^2\right)$ is an iid random innovation in x_t; ε_t^0 is the unanticipated shock and ε_t^1 and ε_t^2 are news shocks. The variable y_t responds to one-period anticipated innovations in x and z_t changes with two-period anticipated innovation in x. One does not observe y_t and z_t separately, but one knows v_t, where

$v_t = y_t + z_t$ and one also observes x_t. Assume ρ_x and ρ_y are given, the econometricians need to estimate the three parameters σ_0, σ_1 and σ_2 with the available observed data on v_t and x_t. It can be done because each of these shocks has a distinct effect on the joint behaviour of the two observables. First, the covariance between v_t and x_{t+1} depends on σ_1, so this moment defines σ_1. Second, the variance of v_t depends on σ_1 and σ_2; σ_2 is identified given σ_1. And third, the variance of x_t depends on σ_0, σ_1 and $\sigma_{2,}$ so this identifies σ_2, given σ_1 and σ_0. Therefore, knowledge of the underlying data generating process should allow successful identification of the volatilities of the three underlying sources of uncertainty. Then they show how Bayesian estimation methods can be used to find these parameters. First, they assume the values for all three parameters, and produce an artificial data set of 250 observations for the observables x_t and v_t. Second, they assume gamma prior distributions for these parameters, and use Bayesian methods to estimate σ_i; this successfully uncovers the true values of the parameters in the model. They apply this method to a real business cycle model with four real rigidities, which has seven structural shocks featuring an anticipated and unanticipated components. The anticipated component is driven by innovations announced four or eight quarters in advance. They find that news shocks about future total factor productivity are negligible sources of fluctuations.

Khan and Tsoukalas (2012) reach a similar conclusion, also using Bayesian methods to estimate a DSGE model with several frictions and both unexpected and news shocks. They find that unanticipated shocks dominate news shocks in explaining the variation in main macroeconomic variables for the post-war period in the US. Fujiwara, Hirose and Shintani (2011) estimate (again by Bayesian methods) a model of news shocks on TFP in a New Keynesian model and find that TFP explains around 20-30% of output fluctuation in the US. While the unexpected TFP components are dominant drivers of the business cycles, the news shocks also are important. As the forecast horizon of the news shocks gets longer, effects of the news shocks on nominal variable become larger.

Gortz and Tsoukalas (2013) 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. It incorporates a final goods and a capital goods sector, each with different sector-specific technologies and co-movements. The final goods sector buys goods from the capital goods sector. If the final goods sector anticipates a permanent increase in its own TFP, it demands more capital from the capital sector and thus this results in higher price of capital. Banks lend to the final goods sector in order to buy capital, but banks themselves face a constraint tied to their equity. The constraint is relaxed due to a higher capital price and allows for more lending and economic stimulation. They estimate the model using Bayesian methods for the US data for the 1990-2011 period. They find that news about the future TFP, the majority of which is the consumption-specific TFP news, explains a large fraction of the business cycle. They reconcile this finding with the structural VAR evidence in various ways. They apply Barsky and Sims (2001)'s identification scheme for the news shocks and compare the responses from the estimated VAR and responses from VARs estimated on artificial samples generated from the structural DSGE model. They find that estimated VAR responses are qualitatively consistent with the model's responses and also that the variance share predicted by the VAR and DSGE models are very similar quantitatively. They also establish that the empirical VAR responses could have been generated from the model. They generate 1000 artificial model samples by drawing parameter values from the posterior distribution and simulated the model. They then compare the empirical VAR IRFs with those generated by identical VAR specifications estimated on the artificial model samples, and find that the former lie within the confidence bands of the latter.

2 Simulating and testing an RE model with news about the future

Models with 'news about future shocks' are asserting a direct link to the future via an unobservable (to the econometrician) current shock. If so, we must assume that this news is acted upon by some agents who observe it, and that this action has effects in some equation, say the investment equation. We can think of these agents as either exactly knowing the future (their R&D programmes (RD_t) tell them what will emerge) or knowing it with some random error. This last situation resembles 'signal extraction' where agents have a current noisy process from which they extract the signal they wish to identify: we may assume that these agents observe past R&D programmes in their firms and their later effects, and thus obtain a statistical relationship from R&D to the later effects such as $u_{t+1} = \gamma RD_t + \varepsilon_{t+1}$. One can then ask what should be their rational expectation, given their failure to have complete future information, of $u_{t+1}, E_t u_{t+1}$. Plainly

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

But if we look at the recent work surveyed above, we find that the news shock has been written as $f(u_{t+1}) + \epsilon_t$ where ϵ_t is a pure i.i.d shock whose variance is unknown and can be found by fitting the model to the data; it is a free variable. However, econometricians can in fact put limits on this variance, even though they cannot observe RD_t. Thus we know that $E_t u_{t+1} = u_{t+1} - \varepsilon_{t+1}$. The two polar limiting possibilities are that agents know u_{t+1} exactly, in which case the variance of ε (and of ϵ) is zero and $f(u_{t+1}) = u_{t+1}$; or that they do not know it at all ($\gamma = 0$) when the variance of ε is the same as that of u and $u_{t+1} = \varepsilon_{t+1}$. But in this last case there is also no news shock and so the variance of ϵ is by definition zero.

It follows that we should write the news shock as $N_t = u_{t+1} - \varepsilon_{t+1}$. The maximum variance of ε is that of u and tends to this as N_t tends to zero; and the minimum variance of ε is zero and tends to this as N_t tends to u_{t+1}. We can represent this relationship between the news shock and its 'true content' as $N_t = \phi u_{t+1} + \epsilon_t$, where in general $var(\epsilon) = \phi(1-\phi)var(u)$.[1] 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. This restriction on the variance of the news shock ϵ needs to be enforced under rational expectations.

It is possible to use other modelling approaches rather than rational expectations, e.g. models of learning, of erroneous beliefs, and of behavioural biases. Such approaches are also testable (e.g. Liu and Minford, 2012). But the point here is that if the models being proposed assume rational expectations, then this implies restrictions on the news errors.

2.1 Testing RE 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 Smets and Wouters (2007) which also

[1] We obtain this as follows. The regression coefficient of u_{t+1} on RD_t is γ where $\gamma = cov(RD, u)/var(RD)$. Then that in the opposite direction, of RD_t on u_{t+1} (which is implicit in the situation even though not directly used by agents with news), is $\gamma \frac{varRD}{varu}$ but contains an error so that $RD_t = \gamma \frac{var(RD)}{var(u)} u_{t+1} + w_t$. Hence $N_t = E_t u_{t+1} = \gamma RD_t = \gamma^2 \frac{var(RD)}{var(u)} u_{t+1} + \gamma w_t$, so that $\phi = \gamma^2 \frac{var(RD)}{var(u)}$.

The variance of $\epsilon_t = \gamma w_t, var(\epsilon)$ is obtained as follows. The explained variance of RD is $\gamma^2 (\frac{var(RD)}{var(u)})^2 var(u) = \gamma^2 (\frac{var(RD)}{var(u)}) var(RD)$. $var(w)$ is the unexplained variance of RD and hence $= (1 - \gamma^2 (\frac{var(RD)}{var(u)})) var(RD) = (1 - \phi)(\frac{var(RD)}{var(u)}) var(u)$. Hence $var(\epsilon) = var(\gamma w) = \gamma^2 var(w) = \gamma^2 (\frac{var(RD)}{var(u)})(1-\phi) var(u) = \phi(1-\phi) var(u)$.

includes flexible goods and labour sectors, a financial sector and money market. The model was tested and estimated with nonstationary data and it has a nonstationary productivity shock. To incorporate 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. We use the Indirect Inference technique on this model to address two issues: one, rather brief, is whether non-invertibility is a problem in the presence of news shocks and the second one, the main question, is whether news shocks contribute much to the business cycle.

On the first issue, if the true model contains news about the future, then its VARMA reduced form will contain a non-invertible MA process. In this case the VAR approximation to it would contain roots that are outside the unit circle and hence there is no finite VAR approximation. As a description of the data we could however use the VARMA in our indirect inference tests; if the DSGE model we are solving contains this news feature, then it too should generate such a description. However, we have in a Monte Carlo experiment embedded a variety of news shocks in our model and generate many samples from it. We find that in no case are we able to generate non-fundamentalness in the resulting VAR. This confirms previous findings noted above (Sims, 2012) that non-fundamentalness in practice is rarely encountered.

We now go on to investigate the role of news shocks according to our model. 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 with data with the transformed Wald statistics of 1.3266 (a value less than 1.645 shows the model is not rejected). Without further reestimation we find that there are some differences in the model's behaviour as shown in the following graphs for some samples of output, investment and consumption. 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 figures 1-3. Also they do not increase significantly the contribution of productivity shocks in explaining the output variation (Table 1).

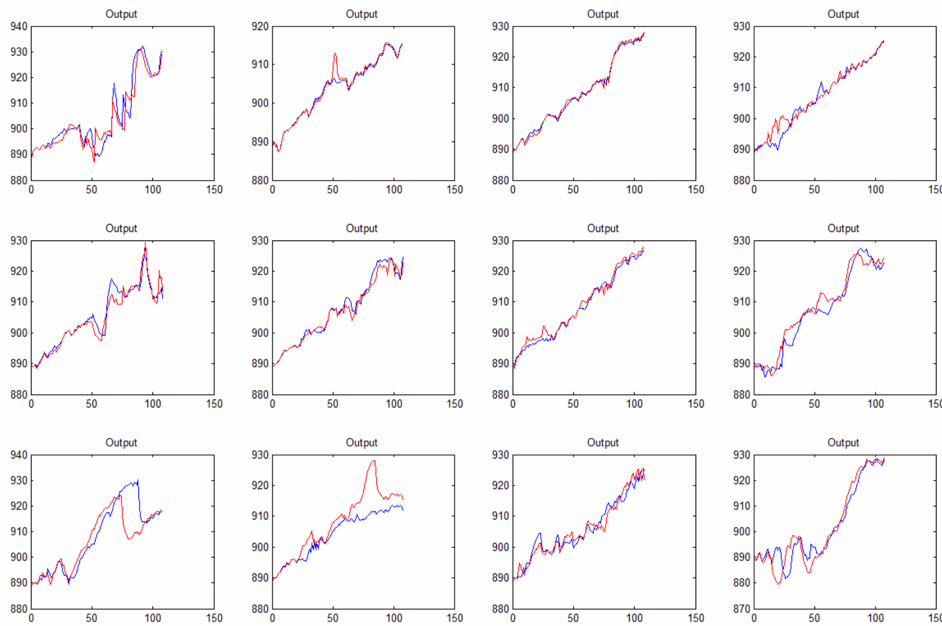

Figure 1: Different samples of output simulation (blue=no news, red=news)

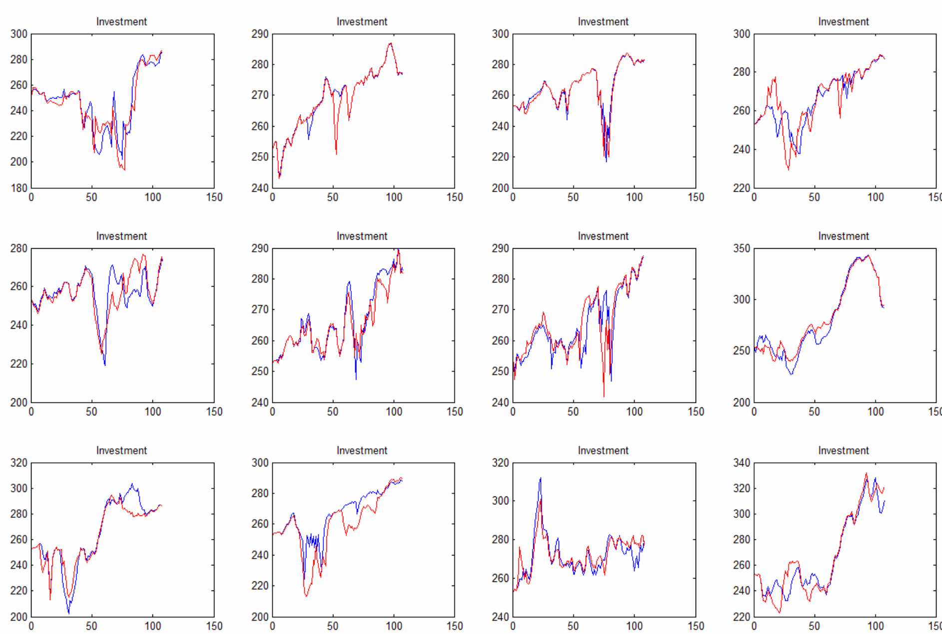

Figure 2: Different samples of investment simulations (blue=no news, red=news)

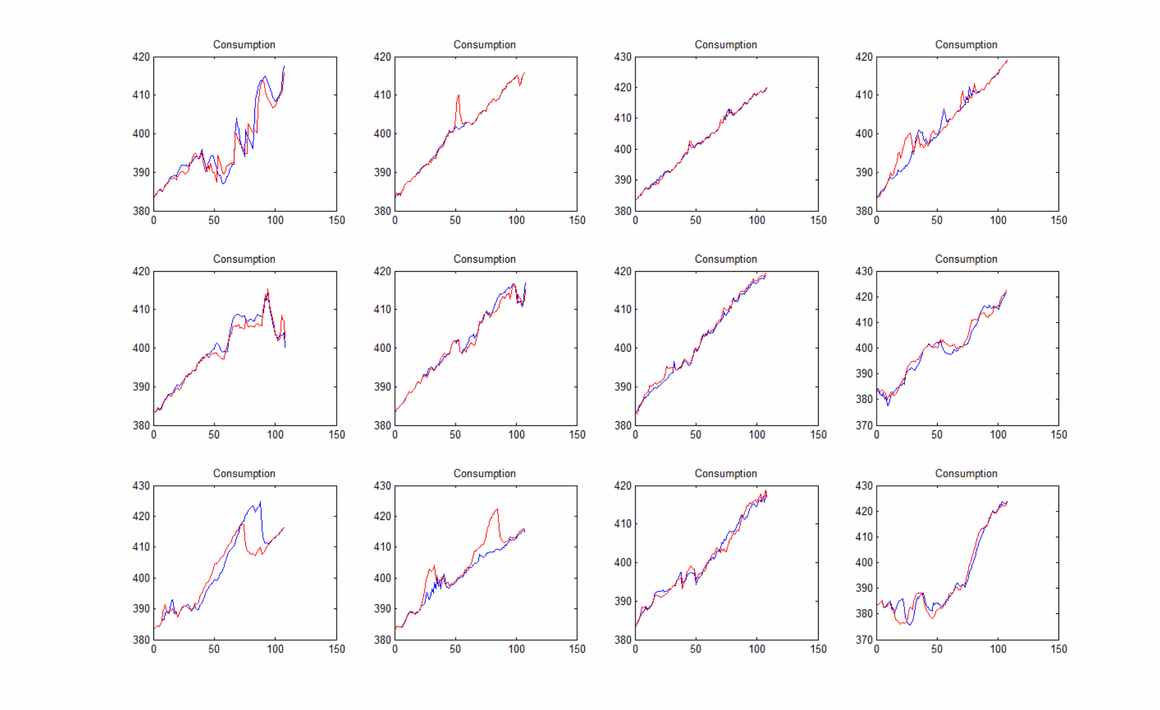

Figure 3: Different samples of consumption simulation (blue=no news, red=news)

Variance decomposition	Model as estimated without news shocks	
Shocks	Output no news	Output with news
Govt Spending	0.87	0.86
Consumer Preference	0.82	0.81
Investment	1.30	1.28
to Interest rate	1.04	1.02
Productivity	84.25	84.49
Price Mark-up	0.18	0.17
Wage Mark-up	0.00	0.00
Labour supply	0.60	0.59
to Premium	2.34	2.30
to Networth	2.39	2.35
Money supply	6.22	6.12
Total	100	100

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

Moreover, 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 from that of the model without news.

Models' Coefficients			
		Estimated Model *without* news	Estimated Model *with* news
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)

Altogether, this study with a DSGE model basically shows that news about future shocks makes only a marginal contribution to explaining the business cycle. This is true whether we reestimate the model or not.

2.2 How to model news shocks?

Our results here tally with almost all the DSGE model papers that have looked at this issue, in that they find a fairly small role for news shocks about the future TFP. Nevertheless in our case the results are totally trivial, whereas in some of these contributions they can be more sizeable. The one exception where much larger effects of news shocks are consistently found is Gortz and Tsoukalas (2013) where news shocks mattered once they inserted a financial channel; we too have a financial channel and yet again the effect of news is trivial.

Why might we be getting this result, that news shocks have only trivial effects? 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 differently.

Consider the following simple case. Let productivity, κ_t, be a random walk: $\kappa_t = \kappa_{t-1} + \epsilon_t$. If 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 then their expectation is

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

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.

What this means is that when one has news shocks one reacts earlier to events; however the reaction is the same. Close inspection of the red (with news) and blue (without news) lines in the figures 1-3 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 V, 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.

Notice that here the news shock (illustrated for one period ahead) is $N_t = \phi u_{t+1} + \epsilon_t$, where in general $var(\epsilon) = \phi(1-\phi)var(u)$. We 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. Effectively, it 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 (2013) 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. Difference in 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 decomposition 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. The 2nd column shows the decomposition when people have exact knowledge of the future shock. The 3rd column shows the case when they have signal extraction and know half the shock 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 but add a random ϵ with unrestricted and progressively higher variance. In these we see clearly how the decomposition changes, with a steadily rising share of TFP shocks as this ϵ variance increases.

	No news	With signal extract TFP shocks only $N_t = u_{t+1}$	With signal extract TFP shocks $N_t = 0.5u_{t+1} + \epsilon_t$ $var(\epsilon) = 0.25var(u)$	With signal extract TFP shocks + random error ϵ (stdev =0.5)	With signal extract TFP shocks + random error ϵ (stdev =0.7)	With signal extract TFP shocks + random error ϵ (stdev =1.0)
Interest rate	3.65	3.93	2.53	4.82	5.56	7.00
Investment	3.89	4.23	3.07	5.38	5.97	7.11
Tobin's q	35.42	36.81	31.54	39.99	41.09	41.59
Capital	1.14	1.39	0.48	2.68	3.55	5.28
Inflation	4.88	5.15	3.03	7.06	8.41	10.78
Wage	55.65	57.35	52.74	62.88	66.16	70.71
Consumption	79.31	79.48	77.76	81.91	83.62	86.11
Output	84.25	84.49	83.09	86.16	87.30	88.98
Hours	12.39	14.77	7.78	23.28	29.26	39.40
Return on Capital	2.01	3.74	1.81	6.36	8.51	12.89
Premium	0.64	0.85	0.40	1.23	1.39	1.64
Networth	2.68	3.29	1.59	4.72	5.43	6.59

Table 3: Contribution of productivity shocks

What this table seems to reveal is that the importance of news shocks 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.

Alternatively, this idea can be shown by looking at Figure 4, where we show the corresponding output IRFs for a future $(t+1)$ TFP shock which is forecast at time t. The diamond line shows the IRF under signal extraction with the variance of ϵ restricted by rational expectations, the shock size is 0.36, which smaller than the case of perfect foresight with the shock size of 0.44 — presented by the solid line. The other lines show the IRFs for three cases of higher ϵ shock variances.

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.

3 Concluding remarks

In this paper we examine the evidence concerning the role of news shocks. By these we mean that agents observe some private data unobservable to the econometrician and this allows them to forecast future (publicly known) shocks by using the past relationships between their private information and the public data on these shocks. We relate the idea of a news shock in a DSGE model to the issue of a non-fundamental VARMA, where the presence of roots greater than unity in the MA process render it non-invertible (so that

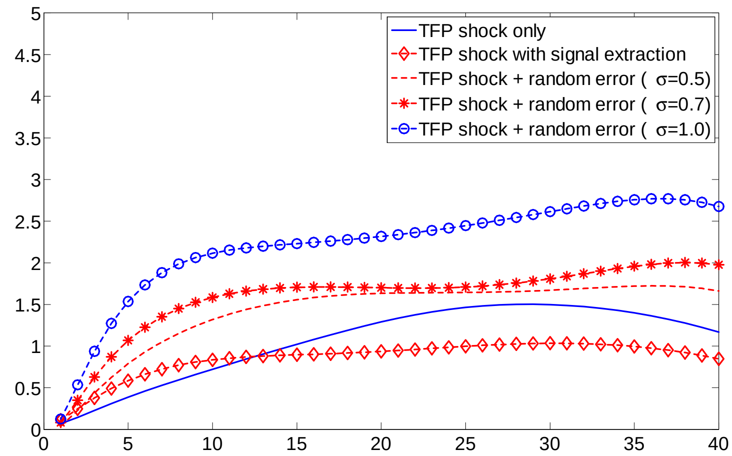

Figure 4: Output's IRFs for different shock assumptions

the econometrician cannot extract the shock as we would expect).

In practice, work in this literature has found little evidence of such roots. 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 more marked effect.

We simulated a version of Smets and Wouters' (2007) model of the US from Le et al. (2016a) which passed stringent indirect inference tests, adding news shocks to it. We found that the model with news about future productivity still passed the tests but was hardly altered by the addition, and that the effects of the these particular news shocks within it were trivial.

Within our model the reason for this is that the news shocks 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. It turns out that other DSGE authors have added to the news shock a random error term representing 'false news'. Depending on how large the variance of this shock is made one can find potentially large effects of it. We show in the paper that adding this error violates rational expectations. Effectively these authors are embedding a sunspot in their models.

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4 Appendix: DSGE Models and their VARMA solution

4.1 Models with a fundamental solution

As already noted DSGE models with standard shocks, current and lagged, generate VARMA solutions of a fundamental type. It will be useful to give an example of this in the form of the familiar three-equation New Keynesian model, where as usual inflation is π, the output gap is y, the short term interest rate is r, the AR error processes are e:

$$\begin{aligned}
\pi_t &= \omega E_t \pi_{t+1} + \lambda y_t + e_{\pi t}, \quad \omega < 1 && (1)\\
y_t &= E_t y_{t+1} - \frac{1}{\sigma}(r_t - E_t \pi_{t+1}) + e_{yt} && (2)\\
r_t &= \gamma \pi_t + \eta y_t + e_{rt} && (3)\\
e_{it} &= \rho_i e_{i,t-1} + \varepsilon_{it} \quad (i = \pi, y, r)
\end{aligned}$$

Re-writing the model using the lag operator $E_t x_{t+1} = L^{-1} x_t$ gives

$$\begin{bmatrix} 1-\omega L^{-1} & -\lambda & 0 \\ -\frac{1}{\sigma}L^{-1} & 1-L^{-1} & \frac{1}{\sigma} \\ -\gamma & -\eta & 1 \end{bmatrix} \begin{bmatrix} \pi_t \\ y_t \\ r_t \end{bmatrix} = \begin{bmatrix} e_{yt} \\ e_{\pi t} \\ e_{rt} \end{bmatrix}. \tag{4}$$

The solution is therefore

$$\begin{bmatrix} \pi_t \\ y_t \\ r_t \end{bmatrix} = \frac{1}{\Delta(L)} \begin{bmatrix} 1+\frac{\eta}{\sigma}-L^{-1} & \lambda & -\frac{\lambda}{\sigma} \\ -\frac{1}{\sigma}(\gamma - L^{-1}) & 1-\omega L^{-1} & -\frac{1}{\sigma}(1-\omega L^{-1}) \\ \gamma - (\gamma - \frac{\eta}{\sigma})L^{-1} & \lambda\gamma + \eta - \eta\omega L^{-1} & (1-\omega L^{-1})(1-L^{-1}) - \frac{\lambda}{\sigma}L^{-1} \end{bmatrix} \times \begin{bmatrix} e_{\pi t} \\ e_{yt} \\ e_{rt} \end{bmatrix} \tag{5}$$

where

$$\begin{aligned}
\Delta(L) &= \frac{\lambda}{\sigma}(\gamma - L^{-1}) + (1-\omega L^{-1})(1+\frac{\eta}{\sigma} - L^{-1})\\
&= (1+\frac{\eta+\lambda\gamma}{\sigma}) - [\frac{\lambda}{\sigma} + \omega(1+\frac{\eta}{\sigma})]L^{-1} + \omega L^{-2}\\
&= [1+\frac{\eta+\lambda\gamma}{\sigma}](1-\lambda_1 L^{-1})(1-\lambda_2 L^{-1})
\end{aligned}$$

As $\omega \leq 1$ and $\gamma > 1$, $\lambda_1\lambda_2 < 1$ and $\lambda_1 + \lambda_2 < 1$ we have $\lambda_1, \lambda_2 < 1$. Using successive forward substitution, the solution can be shown to be

$$z_t = Qe_t \tag{6}$$

where $z_t' = [\pi_t, y_t, r_t]$, $e_t' = [e_{\pi t}, e_{yt}, e_{rt}]$. We can convert this into a VARMA in terms of the ϵ innovations, by multiplying this through with the three AR terms $(1 - \rho_i L)$. It is clear that the MA is fundamental, since all the ρs are less than unity in absolute value.

Notice also that using the Fernandez-Villaverde et al (2007) ABCD method we can simply find the VAR form of the solution:

$$\begin{aligned} z_t &= Az_{t-1} + Be_t \\ e_t &= Ce_{t-1} + D\varepsilon_t \end{aligned} \tag{7}$$

where ε is the vector of innovations in e and $C = P = \begin{bmatrix} \rho_\pi & 0 & 0 \\ 0 & \rho_y & 0 \\ 0 & 0 & \rho_r \end{bmatrix}$; $A = QP; B = Q; D = I$. It follows since $e_{t-1} = Q^{-1}z_{t-1}$ that the VAR solution is:

$$z_t = QPQ^{-1}z_{t-1} + Qe_t = Ez_{t-1} + \eta_t \tag{8}$$

We can also investigate the solution for π_t as an ARMA(3,2):

$$\pi_t = q_{11}e_{\pi t} + q_{12}e_{yt} + q_{13}e_{rt} = q_{11}\frac{\varepsilon_{\pi t}}{1 - \rho_\pi L} + q_{12}\frac{\varepsilon_{yt}}{1 - \rho_y L} + q_{13}\frac{\varepsilon_{rt}}{1 - \rho_r L} \Longrightarrow \tag{9}$$

$$(1-\rho_\pi L)(1-\rho_y L)(1-\rho_r L)\pi_t = q_{11}(1-\rho_y L)(1-\rho_r L)\varepsilon_{\pi t} + q_{12}(1-\rho_\pi L)(1-\rho_r L)\varepsilon_{yt} + q_{13}(1-\rho_\pi L)(1-\rho_y L)\varepsilon_{rt} \tag{10}$$

Thus the solution for π_t conditional on the errors, its own past and y_t is as follows[2]:

[2] Note that y is also an ARMA(3,2) function of the same errors so that if one does attempt to estimate a structural Phillips Curve by replacing y with IV estimates one is faced with the problem that there are no valid instruments since the only variables

$$\pi_t = \omega E_t \pi_{t+1} + \lambda y_t + e_{\pi t} = \omega[q_{11}\rho_\pi \frac{\varepsilon_{\pi t}}{1-\rho_\pi L} + q_{12}\rho_y \frac{\varepsilon_{yt}}{1-\rho_y L} + q_{13}\rho_r \frac{\varepsilon_{rt}}{1-\rho_r L}] + \lambda y_t + \frac{\varepsilon_{\pi t}}{1-\rho_\pi L} \tag{11}$$

$$\begin{aligned}(1-\rho_\pi L)(1-\rho_y L)(1-\rho_r L)\pi_t &= (\omega q_{11}\rho_\pi + 1)(1-\rho_y L)(1-\rho_r L)\varepsilon_{\pi t} + \omega q_{12}\rho_y (1-\rho_\pi L)(1-\rho_r L)\varepsilon_{yt} \\ &\quad + \omega q_{12}\rho_r (1-\rho_\pi L)(1-\rho_y L)\varepsilon_{rt} + (1-\rho_\pi L)(1-\rho_y L)(1-\rho_r L) y_t\end{aligned} \tag{12}$$

4.2 DSGE models with news shocks and a nonfundamental VARMA solution

4.2.1 No News shocks and fundamental solution

Lippi and Reichlin (1994) pointed out that any time-series process with a fundamental MA error element can be converted into one with a non-fundamental MA error by using Blaschke matrices, which create a new white noise error with MA roots that are the inverse of the fundamental MA error's roots. Suppose we have a univariate fundamental MA process

$$y_t = (1-\lambda L)\epsilon_t \text{ where } \lambda < 1 \tag{13}$$

then the non-fundamental equivalent MA process is

$$y_t = (1-\lambda^{-1} L)\eta_t \text{ where } \eta_t = \frac{(1-\lambda L)}{(1-\lambda^{-1} L)}\epsilon_t \tag{14}$$

But this definition cannot be used because it implies an explosive backward series in lagged values. Instead we need to rewrite it as $\eta_t = \frac{-\lambda L^{-1}(1-\lambda L)}{(1-\lambda L^{-1})}\epsilon_t$ - that is, an infinite distributed lead in current and future values of ϵ_t.

This shows that the non-fundamental MA process cannot be a solution of a rational expectations model

correlated with y_t are the current errors and yet these are highly correlated with the equation error. In practice any equation for inflation based on its reduced form has these errors on the right hand side and so includes the determinants of the output gap.

where there is no news about the future. Since expectations of future shocks are zero, they do not enter the solution of the model. The non-fundamental process cannot be constructed, thus there is no equivalent non-fundamental form. Lippi and Reichlin (1994) call this the case where the 'econometrician's and agent's knowledge coincide'; of course in an RE macro model this is assumed to be the case when there is no news about future shocks.

4.2.2 News – Non-fundamental MA process

However if there is news about future shocks, the time-series solution of the model can be non-fundamental. In a model, the news about the future must actually be a current shock, which carries the information about the future event, otherwise people would not react to what they do not observe in the current period. For simplicity, we assume that the news is 100% accurate and it affects p_t and not y_t.The same current shock affects both, while both are subject to the same AR process and output also to a further shock. So:

$$p_t = \lambda p_{t-1} + a_1 e_{t+1} + a_2 e_t \tag{15}$$

$$y_t = \lambda y_{t-1} + b_1 e_t + b_2 w_t \tag{16}$$

Rewrite equation (15) as follows

$$p_t = \lambda p_{t-1} + a_2(1 + \frac{a_1}{a_2} L^{-1}) e_t \text{ with } \frac{a_1}{a_2} < 1 \tag{17}$$

Here apparently p_t depends on its past and a future shock, as well as current shocks. However, notice we could also create a shock, $z_t = e_{t+1}$ and write the equations as:

$$p_t = \lambda p_{t-1} + (1 + \frac{a_2}{a_1} L) z_t \tag{18}$$

$$y_t = \lambda y_{t-1} + b_1 z_{t-1} + b_2 w_t \tag{19}$$

Equation (18) contains a standard MA process except that it is non-invertible as $\frac{a_2}{a_1} > 1$. This is now a non-fundamental ARMA process, because being non-invertible the MA error cannot be recovered from the history of prices.

We now take this further by putting such news about future shocks into the standard NK model.

4.2.3 The New Keynesian (NK) model with news shocks

Consider a simple model in which aggregate demand is set by some exogenous shock process and there is a NK Phillips Curve for inflation:

$$y_t = \epsilon_t/(1-\lambda L) \tag{20}$$

$$\pi_t = \beta E_t \pi_{t+1} + \gamma y_t \tag{21}$$

Solution of NK model with news shocks Assume that there is news at t of ϵ_{t+1} and hence y_{t+1} We can now write the solution for inflation as:

$$\pi_t = E_t \sum_{i=0}^{\infty} \beta^i \gamma y_{t+i} = \gamma y_t + \frac{\gamma\beta}{1-\beta\lambda} y_{t+1} = \gamma(1 + \frac{\lambda\beta}{1-\beta\lambda}) y_t + \frac{\gamma\beta}{1-\beta\lambda}\epsilon_{t+1}. \tag{22}$$

From this substituting from y in terms of ϵ we obtain:

$$(1-\lambda L)\pi_t = \frac{\gamma}{1-\beta\lambda}(1+\beta L^{-1} - \lambda\beta)\epsilon_t = \frac{\gamma\beta}{1-\beta\lambda}(1+\frac{1-\beta\lambda}{\beta}L)\epsilon_{t+1} \tag{23}$$

$$(1-\lambda L)y_t = \epsilon_t. \tag{24}$$

Here we will assume that λ is large enough for $\frac{1-\beta\lambda}{\beta} < 1$. Now simply write $v_t = \epsilon_{t+1}$ and we have a simple VARMA (fundamental) solution:

$$(1-\lambda L)\pi_t = \frac{\gamma\beta}{1-\beta\lambda}(1+\frac{1-\beta\lambda}{\beta}L)v_t \tag{25}$$

$$(1 - \lambda L)y_t = \epsilon_t \tag{26}$$

We may then identify v_t, ϵ_t from the structural model as being respectively $\epsilon_{t+1}, \epsilon_t$. The point is that the news about the future shock is a current event and so rightly appears as a current shock in the VARMA. We can think of the effect of aggregate demand shocks on inflation as occurring first as news and second as fact.

Alternatively we can write the model solely in terms of the ϵ shock and we obtain:

$$(1 - \lambda L)\pi_t = \gamma(1 + \frac{\beta}{1 - \beta\lambda} L^{-1})e_t \tag{27}$$

$$(1 - \lambda L)y_t = \epsilon_t \tag{28}$$

This reveals that the MA process on ϵ in inflation is non-invertible into the future. If we lag the inflation equation, we obtain the (backwards-)invertible form

$(1 - \lambda L)\pi_{t-1} = \frac{\gamma\beta}{1-\beta\lambda}(1 + \frac{1-\beta\lambda}{\beta} L)e_t$

We see from this that in this model last period's inflation was determined before today's period opened, by today's shock.

This is an example of a model with a news shock that still produces a fundamental VARMA.

A non-invertible MA solution for the NK model To illustrate a case where we obtain a non-invertible MA, let the model be the same except that now there is a news shock in the NK Phillips Curve, whereas the demand shock is not subject to news. Suppose the demand shock is the same autocorrelated process as before, but that the supply shock is iid. So we have:

$$y_t = \epsilon_t/(1 - \lambda L) \tag{29}$$

$$\pi_t = \beta E_t \pi_{t+1} + \gamma y_t + u_t \tag{30}$$

The solution for output y_t is the same as before, but the solution for inflation is

$$\pi_t = \frac{\gamma}{1-\beta\lambda}[\epsilon_t/(1-\lambda L)] + \beta u_{t+1} + u_t = \lambda\pi_{t-1} + \frac{\gamma}{1-\beta\lambda}\epsilon_t + (1+\beta^{-1}L)(1-\lambda L)v_t$$

where $v_t = u_{t+1}$ and the MA process on v_t is non-invertible. This is occurring because the effect of the news shock from the future on today is less than the current effect of u today - which in general is of course a perfectly possible situation.