BANK OF ENGLAND

Working Paper No. 488

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March 2014

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Abstract

This paper uses a vector autoregression model estimated with Bayesian methods to identify the effect of productivity news shocks on labour market variables by imposing that they are orthogonal to current technology but they explain future observed technology. In the aftermath of a positive news shock, unemployment falls, whereas wages and the job finding rate increase. The analysis establishes that news shocks are important in explaining the historical developments in labour market variables, whereas they play a minor role for movements in real activity. We show that the empirical responses to news shocks are in line with those of a baseline search and matching model of the labour market and that the job destruction rate and real wage rigidities are critical for the variables' responses to the news shock.

Key words: Anticipated productivity shocks, Bayesian SVAR methods, labour market search frictions.

JEL classification: E32, C32, C52.

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We thank Robert Barsky and Eric Sims for providing us with their data. We would like to thank Paul Beaudry, Wouter den Haan, Charlotte Dendy, Monique Ebell, Lydia Silver and seminar participants to the Bank of England, London School of Economics and University of Oxford for extremely helpful comments and suggestions. This paper represents the views and analysis of the authors and should not be thought to represent those of the Bank of England. This paper was finalised on 20 January 2014.

The Bank of England's working paper series is externally refereed.

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Publications Group, Bank of England, Threadneedle Street, London, EC2R 8AH
Telephone +44 (0)20 7601 4030 Fax +44 (0)20 7601 3298 email publications@bankofengland.co.uk

ISSN 1749-9135 (on-line)

Summary

A number of studies establish that anticipated changes in future productivity, referred to as news shocks, represent an important source of business cycle fluctuations. Many authors have focused on the effect of news on economic activity, but none so far have investigated the effect on labour market variables. This paper fills this gap. It develops a multivariate statistical model that identifies the effect of anticipated productivity shocks on unemployment, wages and the job finding probability, and it then investigates to what extent a simple theoretical model with real frictions on the labour market is able to replicate the empirical impact of news shocks on labour market variables and macroeconomic aggregates.

In the aftermath of a positive news shock, unemployment falls, whereas wages and the job finding probability increase. The inclusion of labour market variables does not alter the response of macroeconomic aggregates to the news shock, since output and investment modestly fall and consumption increases, in line with recent studies that abstract from labour market variables. We establish using US data that news shocks explain 30% of unemployment fluctuations and approximately 20% of the job finding rate, whereas their contribution to output and consumption is more limited to around 15% in the long run. We also illustrate that most of the historical fluctuations in the job finding rate and unemployment are explained by news shocks, whereas news shocks play a limited role in explaining wages and output fluctuations.

We next set up a simple theoretical model with real (search and matching) distortions in the labour market. We find that this basic framework replicates the news shocks identified in the data relatively well. The theoretical model shows that in response to a positive news shock the firm anticipates that the surplus from establishing a match increases, thereby leading to an increase in vacancy posting that generates a decrease in unemployment. High vacancy posting and low unemployment raise labour market tightness, which increases the job finding rate. In general, the qualitative responses are similar to those from the time-series model. However, the responses of unemployment and wages to a news shock are not in line with those predicted by the empirical model. Hence, we investigate to what extent refinements to the basic framework improve the model's performance. We establish that the job destruction rate and real wage rigidities are important for the response of unemployment and wages to the news shock and for the overall variables' responses.

1 Introduction

A number of studies establish that anticipated changes in future productivity, referred to as news shocks, represent an important source of business cycle fluctuations.[1] Extensive research has focused on the effect of news on economic activity, but no studies have so far investigated its effect on labour market variables. This paper fills this gap. It develops a VAR-based scheme that identifies the effect of anticipated productivity shocks on unemployment, wages and the job finding probability, and it then investigates to what extent a standard search and matching model of the labour market is able to replicate the empirical impact of news shocks on labour market variables and macroeconomic aggregates.

The identification of news shocks is based on Barsky and Sims (2011) and implemented using Bayesian methods. It assumes that a news shock explains a sizeable fraction of the movements in future productivity but has no impact on current productivity. This approach imposes a minimum of theoretical restrictions relative to other identification schemes, either based on long-run or sign restrictions in VAR models, as in Beaudry and Portier (2004) and Beaudry and Portier (2006), or on general equilibrium models, as in Schmitt-Groh and Uribe (2012) and Khan and Tsoukalas (2012). Once we impose our identifying restrictions on a VAR model that includes key labour market variables, we find that news shocks play an important role for labour market aggregates and the variables' reactions to news shocks are robust across the different identification schemes. In particular, in the aftermath of a positive news shock, unemployment falls, whereas wages and the job finding probability increase. In addition, the inclusion of labour market variables does not alter the response of macroeconomic aggregates to the news shock, since output and investment modestly fall and consumption increases, in line with recent studies that abstract from labour market variables. The VAR model also enables some additional novel analysis. In particular, we use the model to study the contribution of news shocks to movements in the data at different time horizons. We establish that news shocks explain 30 percent of unemployment fluctuations and approximately 20 percent of the job finding rate, whereas their contribution to output and

[1] See Beaudry and Portier (2013) and references therein for a recent review on the literature.

consumption is more limited to around 15 percent in the long run. In addition, we use the model to investigate to what extent news shocks explain historic movements in the data. We establish that most of the historical fluctuations in the job finding rate and unemployment are explained by news shocks, whereas news shocks play a limited role in explaining wages and output fluctuations.

As part of this study, we investigate the implications of identified news shocks on macroeconomic modelling. With this aim, we set up a simple search and matching model of the labour market with news shocks and find that this basic framework replicates the identified news shocks in the data relatively well. The theoretical model shows that in response to a positive news shock the firm anticipates that the surplus from establishing a match increases, thereby leading to an increase in vacancy posting that generates a decrease in unemployment. High vacancy posting and low unemployment raise labour market tightness, which increases the job finding rate. In general, the qualitative responses are similar to those from the VAR model. However, the responses of unemployment and wages to a news shock lie outside the VAR model's confidence band after four quarters. Hence, we investigate to what extent refinements to the basic framework improve the model's performance. We establish that the job destruction rate and real wage rigidities are important for the response of unemployment and wages to the news shock and for the overall variables' responses.

Before proceeding with the analysis, we describe the context provided by related studies. The view that expectations generate economic fluctuations has been recently revisited in a series of influential papers by Beaudry and Portier (2004), Beaudry and Portier (2006) and Barsky and Sims (2011), who develop VAR methodologies to identify the effect of news shocks on economic activity. In addition, Kurmann and Otrok (2013) also use a similar VAR methodology to show that news shocks provide strong linkages between the yield curve, inflation, and real output. This analysis is complemented by recent studies by Schmitt-Groh and Uribe (2012), Khan and Tsoukalas (2012) and Gortz and Tsoukalas (2011), who identify and estimate news shocks in the context of fully-specified general equilibrium models. Our paper contributes to both realms of research by identifying the effect of news shocks on labour market aggregates in the context of a VAR model estimated with Bayesian methods and then

studying to what extent a fully-specified general equilibrium model with labour market search and matching frictions is able to replicate the identified empirical regularities of news shocks. Differently from the existing studies, we extend the analysis to identify the effect of news shocks on labour market aggregates both in the data and in the theoretical model.

This paper also contributes to the realm of research that investigates to what extent news shocks improve the performance of theoretical models in matching business cycle fluctuations. Influential studies by Jaimovich and Rebelo (2009), Den Haan and Kaltenbrunner (2009), and Karnizova (2010), show that news shocks improve the empirical performance of theoretical models, but they also point out that standard real business cycle models are unable to generate positive comovements of macroeconomic aggregates in response to news shocks, therefore they propose different modifications to address this shortcoming. Similarly to our paper, Den Haan and Kaltenbrunner (2009) find that labour market frictions enhance the performance of the model in matching the reactions of consumption, output and investment in response to news shocks. Our analysis is substantially different in three ways. First, ours is the first study that provides an empirical identification of the effect of news shocks on labour market variables, namely wages, unemployment and the job finding rate. Second, we extend the analysis to evaluate how the theoretical model matches the responses of these labour market variables, in addition to consumption, output and investment. Third, our theoretical findings are more general as we use a baseline search and matching model, whereas these authors develop a model with endogenous labour force participation. Our analysis shows that a standard model with labour market search and matching frictions is able to replicate the impact of news shocks on labour market variables and macroeconomic aggregates fairly well. In this respect, our results are related to and reinforce the findings in Leeper and Walker (2011) and Barsky and Sims (2011), which suggest that real business cycle models are able to replicate the responses of macroeconomic aggregates to news shocks, without any need to depart from the standard framework. In addition, our empirical analysis suggests that Pigou cycles (i.e. the contemporaneous comovements of output, consumption and investment) materialize once the news shock realizes, rather than in the anticipation phase.

The remainder of the paper proceeds as follows. Section 2 describes the VAR model,

the methodologies used to identify news shocks, the empirical findings and performs some robustness analysis. Section 3 lays out the theoretical model based on search and matching frictions in the labour market and details its solution and estimation. Section 4 describes to what extent the theoretical model replicates the impact of news shocks in the data and is able to reproduce key business cycle statistics. This section also performs sensitive analysis. Finally, Section 5 concludes.

2 The empirical model

In this section, we describe the empirical model, its estimation using Bayesian methods and how we identify the productivity news shock in the data. We then investigate the effect of news shocks on labour market aggregates across several dimensions.

The empirical model is a vector autoregressive (VAR) model of order K:

$$\mathcal{Y}_t = \sum_{i=1}^{K} \Theta \mathcal{Y}_{t-i} + \nu_t, \tag{1}$$

where ν_t is a $N \times 1$ vector of reduced-form errors that is normally distributed with zero mean and Σ variance-covariance matrix. The regression-equation representation of this system is

$$\mathcal{Y} = X\Theta + V \tag{2}$$

where $\mathcal{Y} = [\mathcal{Y}_{k+1}, .., \mathcal{Y}_T]$ is a $N \times T$ matrix containing all the data points in $\mathcal{Y}_t$, $X = \mathcal{Y}_{-k}$ is a $(NK) \times T$ matrix containing the k-th lag of $\mathcal{Y}$, $\Theta = \begin{bmatrix} \Theta_1 & \cdots & \Theta_K \end{bmatrix}$ is a $N \times (NK)$ matrix, and $\nu = [\nu_{k+1}, .., \nu_T]$ is a $N \times T$ matrix of disturbances.

The dimension of the vector $\mathcal{Y}$ and the number of lags used in the estimation implies that classical inference methods deliver estimates with sizeable uncertainty, given the large number of parameters to estimate. Hence, we use Bayesian methods, as they are a useful alternative approach to reducing estimation uncertainty. In particular, the Minnesota prior shrinks the VAR(K) model to N independent autoregressive models of order one (AR(1)), which reduces estimation uncertainty, as detailed in Doan, Litterman and Sims (1984) and

Litterman (1986). In addition, Banbura, Giannone and Reichlin (2010) illustrates that the model has good forecasting properties. We achieve posterior inference as follows.[2] We assume that the prior distribution of the VAR parameter vector has the Normal-Inverted-Wishart conjugate form

$$\theta|\Sigma \sim N(\theta_0, \Sigma \otimes \Omega_0),\ \Sigma \sim IW(v_0, S_0), \tag{3}$$

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

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

and, as is explained by Banbura et al. (2010), they can be constructed using the following dummy observations:

$$Y_D = \begin{pmatrix} \frac{diag(\delta_1\sigma_1 ... \delta_N\sigma_N)}{\overline{\omega}} \\ 0_{N\times(K-1)N} \\ ..... \\ diag\,(\sigma_1 ... \sigma_N) \\ ..... \\ 0_{1\times N} \end{pmatrix} \text{ and } X_D = \begin{pmatrix} \frac{J_K \otimes diag(\sigma_1 ... \sigma_N)}{\overline{\omega}} \\ 0_{N\times NK} \\ ..... \\ 0_{1\times NK} \end{pmatrix}, \tag{4}$$

where $J_K = diag\,(1, 2, ..., K)$ and $diag$ denotes the diagonal matrix. The prior moments of (3) are functions of Y_D and X_D, $\Theta_0 = Y_D X_D' (X_D X_D')^{-1}$, $\Omega_0 = (X_D X_D')^{-1}$, $S_0 = (Y_D - \Theta_0 X_D)(Y_D - \Theta_0 X_D)'$, $v_0 = T_D - NK$, and $T_D = NK + 3$. Finally, the hyper-parameter $\overline{\omega}$ controls the tightness of the prior.

Since the Normal-Inverted-Wishart prior is conjugate, as shown in Kadiyala and Karlsson (1997), the conditional posterior distribution of this model is also Normal-Inverted-Wishart

$$\theta|\Sigma, Y \sim N(\bar{\theta}, \Sigma \otimes \bar{\Omega}),\ \Sigma|Y \sim IW(\bar{v}, \bar{S}), \tag{5}$$

[2]See Mumtaz and Zanetti (2012) and references therein for additional details on the estimation procedure.

where the bar denotes the parameters of the posterior distribution. Defining $\hat{\Theta}$ and $\hat{U}$ as OLS estimates, it yields $\bar{\Theta} = (\Omega_0^{-1}\Psi_0 + YX')(\Omega_0^{-1} + X'X)^{-1}$, $\bar{\Omega} = (\Omega_0^{-1} + X'X)^{-1}$, $\bar{v} = v_0 + T$, and $\bar{S} = \hat{\Theta}XX'\hat{\Theta}' + \Theta_0\Omega_0^{-1}\Theta_0 + S_0 + \hat{U}\hat{U}' - \bar{\Theta}\bar{\Omega}^{-1}\bar{\Theta}'$. The values of the persistence parameter δ_i and the error standard deviation parameter σ_i of the *AR(1)* model are obtained from OLS estimation.

2.1 The identification of news shocks

We identify the news shocks using a similar scheme to Barsky and Sims (2011) and Kurmann and Otrok (2013). In particular, we assume that productivity is driven by two shocks: the unanticipated productivity shock, $\varepsilon_{a,t}$, and the anticipated news shock, $\varepsilon_{\psi,t-j}$, where j indicates the anticipation horizon. Hence, technology a can be expressed as

$$\ln a_t = \rho_A \ln a_{t-1} + \varepsilon_{a,t} + \varepsilon_{\psi,t-j}. \tag{6}$$

Equation (6) shows that a univariate model is unable to recover the impact of the news shock, since a news shock that occurs today has an effect on technology in the j-ahead period, leaving the current technology unchanged. However, other variables may react instantaneously to the news shock, since rational expectations induce agents to react in advance to future anticipated shocks in order to maximize lifetime utility. Hence, we identify the effect of the news shock by employing a multivariate VAR model, which include variables that react to the news shock on impact. In addition, we identify news shocks by assuming that they explain future movements in TFP not accounted for by the unanticipated technology shock.

To implement this identification in the VAR model we proceed as follows. The moving average representation of the VAR(K) model is

$$\mathcal{Y}_t = B(L)\, v_t. \tag{7}$$

The mapping between the reduced-form errors and the structural shocks is:

$$v_t = A\varepsilon_t, \tag{8}$$

with $AA' = \Sigma$, and the h steps ahead forecast error can be expressed as

$$\mathcal{Y}_{t+h} - E_{t-1}\mathcal{Y}_{t+h} = \sum_{\tau=0}^{h} B_\tau \tilde{A} D \varepsilon_{t+h-\tau}, \tag{9}$$

where $\tilde{A}$ is the lower triangular matrix derived from the Cholesky decomposition of Σ, and D is an orthonormal matrix such that $DD' = I_{d\mathcal{Y}}$, where $I_{d\mathcal{Y}}$ is the $d\mathcal{Y} \times d\mathcal{Y}$ identity matrix. The contribution of the structural shock j to the forecast variance of variable i at horizon h is

$$FVD_{i,j}(h) = \frac{e_i' \left(\sum_{\tau=0}^{h} B_\tau \tilde{A} D e_j e_j' D' \tilde{A}' B_\tau' \right) e_i}{e_i' \left(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau' \right) e_i} = \frac{\sum_{\tau=0}^{h} B_{i,\tau} \tilde{A} \gamma \gamma' \tilde{A}' B_{i,\tau}'}{\sum_{\tau=0}^{h} B_{i,\tau} \Sigma B_{i,\tau}'}, \tag{10}$$

where e_i denotes the selection vector with one in the i-th place and zeros elsewhere. We place $\varepsilon_{a,t}$ into the first element of the ε_t vector, and $\varepsilon_{\psi,t-1}$ in to the second one. The assumption that TFP is solely driven by unanticipated and anticipated shocks, as in equation (6), implies that $\varepsilon_{a,t}$ and $\varepsilon_{\psi,t-1}$ account for all variation in TFP at different horizons, which yields:

$$FVD_{1,1}(h) + FVD_{1,2}(h) = 1. \tag{11}$$

However, it is unlikely that equation (11) holds at all horizons in a multivariate VAR model. Hence, as suggested by Barsky and Sims (2011), we select the second column of the impact matrix $\tilde{A}D$ that comes as close as possible to making equation (11) hold over a finite set of horizons. This is achieved by solving the following optimization problem:

$$\gamma^* = \arg\max \sum_{h=0}^{H} FVD_{1,2}(h) \tag{12}$$

subject to

$$\tilde{A}(1,j) = 0 \;\forall\; j > 1, \tag{13}$$

$$\gamma(1,1) = 0, \tag{14}$$

$$\gamma'\gamma = 1. \tag{15}$$

Equations (13) and (14) ensure that TFP does not respond contemporaneously to news shocks, while equation (15) implies that γ^* is a column vector that belongs to an orthonormal matrix D. Furthermore, the first two equations make $FVD_{1,1}(h)$ independent from the selection of γ and, consequently, this term drops from the objective function.

In the empirical exercise h is set equal to 40, which is the same value used by Barsky and Sims (2011), but we also provide results for h equal to 80 and 120. In order to derive the posterior distribution of the responses and the forecast decomposition the identification schemes are implemented for each posterior draw.

2.2 News shocks in the data

This section describes the variables' estimated responses to news shocks, it reports the forecast error variance of the variables attributable to the news shock at different time horizons and presents the variables' historical decomposition over the sample period.

To implement the estimation, we include six variables in the VAR model: total factor productivity (TFP), consumption, output, unemployment rate, real wages and the job finding probability. The series are quarterly US data, seasonally adjusted, and cover the period 1960:Q1-2007:Q1. We specify the VAR with three lags ($K = 3$), but results are robust to higher lags order. Finally, the parameter $\overline{\omega}$ is set equal to 4, implying relatively loose priors. The Appendix provides a detailed description of the data.

Figure 1 shows the estimated impulse response functions (solid line) and the 16-84 percent confidence interval (shadowed area) to the news shock. In the aftermath of the news shock, productivity reaches its peak of 0.2 percent after three quarters and its effect disappears after approximately two years. Given the increase in productivity, consumption rises on impact by approximately 0.12 percent, and declines slowly afterwards. The rise in consumption is mirrored by a fall in both output and investment.[3] In the labour market, in reaction to the news shock, unemployment falls on impact and the effect of the shock on this variable remains strong over the three-year horizon. In the aftermath of the news shock, the job

[3]As in Barsky and Sims (2011), the investment response is imputed as output less the share-weighted consumption response, where it is assumed that consumption is 70 percent of output, which is in line with the data.

finding rate increases on impact and remains positive over the sample period, whereas wages display a weak positive reaction that quickly reverts to zero. These estimated responses show that news shocks have a sizeable and significant impact on labour market variables. Moreover, including labour market aggregates in the VAR model generates a negative response in output and investment, and a positive response in consumption, thereby supporting the findings in the recent study by Barsky and Sims (2011) that undertakes a similar analysis but abstracts from labour market dynamics. It is worth noting that the comovement between output and consumption is negative in the anticipation phase of the news shock, but it then becomes positive once the shock realizes, thereby showing that Pigous' cycles show up in the data but with a one year delay. To provide further evidence on the robustness of these estimates, Figure 2 shows that impulse response functions are very similar across different forecast horizons (40, 80 and 120 quarters).

Figure 3 shows the fraction of the forecast error variance of the variables in the VAR model attributable to the news shock at different horizons. The shadowed area represents the 16-84 percent confidence interval of the posterior distribution. News shocks account for approximately 18 percent of movements in the technological process in the short-run. Similarly, they account for around 15 percent of fluctuations in output and consumption in the long-run, whereas they explain approximately 5 and 10 percent respectively in the short-run. With respect to labour market variables, news shocks explain a sizeable fraction of movements in unemployment, as they account for approximately 5 percent of fluctuations in the short-run, although their contribution increases to 30 percent in the long-run. News shocks explain approximately 5 percent of high frequency movements in the job finding rate, and their contribution increases to 20 percent over the ten-year horizon. Finally, news shocks explain around 10 percent of wage fluctuations in the long-run. These findings reveal both similarities and differences relative to the existing literature. In particular, with the inclusion of labour market variables in the VAR model, the explanatory power of news shocks on economic activity declines in the long-run. Beaudry and Lucke (2010) and Barsky and Sims (2011) find that half of output and consumption fluctuations are explained by news shocks, whereas in our model news shocks explain approximately one fifth of fluctuations in these

variables. However, whereas in the above mentioned studies news shocks are irrelevant for movements in labour input at any horizon, we establish that news shocks explain a sizeable portion of movements in unemployment and the job finding rate in the long-run. This finding echoes the result in Khan and Tsoukalas (2012) who use a general equilibrium model to establish that restricting the labour supply elasticity increases the explanatory power of news shocks on labour input and decreases the importance of news shocks on economic activity. Our analysis reaches a similar conclusion in the context of a VAR model that accounts for labour market variables. Our results are also consistent with Schmitt-Groh and Uribe (2012) who show that when a broader set of shocks compete in an estimated general equilibrium model to explain movements in the data, the importance of news shocks as sources of business cycles declines. Consequently, similarly to these studies based on general equilibrium models, our analysis establishes that, in the context of a VAR model that accounts for labour market variables, news shocks play only a limited role as sources of aggregate fluctuations in economic activity. Figure 4 shows that the results are robust across different forecast horizons (40, 80 and 120 quarters).

It is interesting to use the VAR model to derive the variables' historical decomposition over the sample period. In this way, we can study how news shocks contribute to observed movements in the data. Each entry in Figure 5 reports the historical decompositions that display the contribution of news shocks to movements in output, consumption, unemployment, wages and the job finding probability over the period 1960:Q1-2007:Q1. A number of interesting facts stand out. First, while for most of the sample period news shocks have a limited impact on output and consumption, their relevance increases over the periods 1960-1970, 1988-1994 and 2000-2007, as they contribute to the bulk of movements in these variables. Second, news shocks are important for fluctuations in the job finding and unemployment rates over the periods 1960-1974, and 1988-2007, and their contribution declines over the rest of the sample period. In particular, the contribution of news shocks is the lowest during the period 1975-1985, which coincides the oil shock period. In addition, the contribution of news shocks to unemployment is positive from the early 2000s onwards, but unemployment declines during the same period. Finally, news shocks play a minimal role in historic movements in

wages over the sample period. At this stage we can draw some interesting observations. News shocks are an important source of fluctuations in unemployment and the job finding rate but they have a limited influence on wage fluctuations.[4]

Finally, Figure 6 plots the estimated series of the news shock from the VAR against the recession dates as defined by the NBER business cycle dating committee. The figure shows that, in general, recession periods are not characterized by negative news shocks, since only three out of seven recession periods experienced higher than average news shocks. This correlation structure is consistent with the patterns observed in the estimated historical decomposition, which show that news shocks play a limited role on the dynamics of output over the sample period.

2.3 Robustness analysis

In order to establish whether the results are robust to perturbations to the benchmark specification of the model, we undertake a number of additional robustness checks. In particular, we test whether results are robust to alternative lag structures in the VAR system and find that the variables' reactions to the news shock remain unchanged. We also establish that the results hold if we use alternative measures of the TFP process, which do not correct the Solow residual for the utilization-adjusted TFP measure proposed by Basu, Fernald and Kimball (2006), or if we include stock prices or a measure of the relative price of investment, since the identification scheme may potentially attribute movements in the investment-specific technological change to news shocks.[5] An Appendix that details the robustness of the results is available upon request from the authors.

Finally, we investigate the robustness of our identification method. Hence, we compare our results with the alternative identification scheme of news shocks based on Francis, Owyang, Roush and DiCecio (2012), as also implemented in Beaudry, Nam and Wang (2011). Their identification method has two key differences from the scheme used in our paper. First, it

[4]This might be evidence that real wage rigidities prevent productivity news shocks to fully affect movements in wages. For this reason, we use the theoretical model to investigate the role of real wage rigidities for the propagation of news shocks.

[5]The relative price of investment is constructed using different measures of the investment price deflator divided by different measures of the consumption price deflator, as shown in Fisher (2006).

relaxes the assumption that TFP is driven by the unanticipated productivity shock and the anticipated news shock and it allows other shocks to contribute to the evolution of productivity at least at a finite horizon. Second, it identifies TFP news shocks by maximizing their contribution to the forecast variance decomposition of TFP at a finite horizon h, whereas our scheme identifies news TFP shocks by maximizing their contribution to the forecast variance decomposition of TFP over all horizons up to a finite truncation horizon H. Algebraically, the problem is expressed as follows

$$\gamma^* = \arg\max FVD_{1,2}(h) \tag{16}$$

subject to

$$\tilde{A}(1,2) = 0, \tag{17}$$

$$\gamma(1,1) = 0, \tag{18}$$

$$\gamma'\gamma = 1. \tag{19}$$

Equations (17) and (18) ensure that the news shock has no contemporaneous effect on TFP, and equation (19) implies that γ^* is a column vector that belongs to an orthonormal matrix D. Note that equations (17) and (18) make $FVD_{1,1}(h)$ independent from the selection of γ and, consequently, this term is not included in the objective function (16).

Figure 7 shows the estimated impulse response functions to the news shock using the identification strategies proposed in our paper (solid line) and Francis et al. (2012) (dashed line) for different forecast horizon (i.e. 40, 80 and 120 quarters). The variables' responses are similar across the two identification methods irrespective of the forecast horizon, suggesting that news shocks are consistently and robustly estimated once labour market variables are included in the system.[6]

[6]Note that the reaction of wages to a news shock seems different across the identification methods. However, as in the benchmark model, the response of wages is insignificantly different from zero.

3 The theoretical model

We now set up a simple general equilibrium model with labour market search and matching frictions. We introduce a matching process for hiring in the labour market, as in the Mortensen-Pissarides model, similar to Den Haan and Kaltenbrunner (2009) and Thomas (2011), and we enrich the model with anticipated news shocks, as in Schmitt-Groh and Uribe (2012) and Khan and Tsoukalas (2012).

The model economy is populated by three agents: households, firms and a passive fiscal authority. Households consist of a large number of members, a fraction of which are unemployed and searching for jobs. On the other side of the labour market, firms hire workers by posting vacancies. The fiscal authority balances the budget in every period with lump-sum transfers. The rest of this section describes the agents' tastes, technologies, and the structure of the labour market in detail.

3.1 Firms

Employment relationships are taken to consist of two agents, a worker and a firm, which engage in production through discrete time until the relationship is severed. Firms post a number of vacancies. Unemployed workers and vacancies, which are denoted by u_t and v_t respectively, meet in the so-called matching function, $m(v_t, u_t)$. Normalizing the size of the labour force to 1, u_t also represents the unemployment rate, and $u_t \equiv 1 - n_t$. Under the assumption of constant returns to scale in the matching function, the matching probabilities for unemployed workers,

$$\frac{m(v_t, u_t)}{u_t} = m\left(\frac{v_t}{u_t}, 1\right) \equiv p\left(x_t\right),$$

and for vacancies,

$$\frac{m(v_t, u_t)}{v_t} = m\left(1, \frac{1}{v_t/u_t}\right) \equiv q\left(x_t\right),$$

are functions of the ratio of vacancies to unemployment, $x_t \equiv v_t/u_t$, also called labour market tightness. Notice that $p'\left(x_t\right) > 0$ and $q'\left(x_t\right) < 0$, i.e. in a tighter labour market jobseekers are more likely to find jobs and firms are less likely to fill their vacancies. Notice also that

$p(x_t) = x_t q(x_t)$.

The law of motion of the firm's workforce, n_t, is therefore given by

$$n_t = (1 - \delta_n) n_{t-1} + q(x_t) v_t, \tag{20}$$

where δ_n is the job destruction rate $0 < \delta_n < 1$, and $q(x_t)v_t$ is the number of new matches at time t.

The firm's production function is given by

$$y_t = a_t k_t^{\theta} n_t^{1-\theta}, \tag{21}$$

where a_t is the neutral technology shock, which follows the autoregressive process

$$\ln a_t = \rho_a \ln a_{t-1} + \psi_{t-1} + \varepsilon_{a,t}, \tag{22}$$

and

$$\psi_t = \rho_\psi \psi_{t-1} + \varepsilon_{\psi,t}, \tag{23}$$

with $0 < (\rho_a, \rho_\psi) < 1$, and where the zero-mean, serially uncorrelated innovations $\varepsilon_{a,t}$ and $\varepsilon_{\psi,t}$ are normally distributed with standard deviation σ_a and σ_ψ. In this notation, $\varepsilon_{a,t}$ represents the unanticipated shock to the technological progress, whereas $\varepsilon_{\psi,t}$ represents the anticipated $t+1$ periods ahead news shock, since this term has no contemporaneous effect on the level of technology. As in Barsky and Sims (2011), the parameter ρ_ψ represents the rate of news diffusion.

3.1.1 Profit maximization

Subject to equations (20) and (21), the firm maximizes its profits,

$$E_0 \sum_{t=0}^{\infty} \beta^t \lambda_t \left[y_t - n_t w_t - k_t q_t^k - v_t g_t \right], \tag{24}$$

where $\beta^t \lambda_t$ measures the marginal utility value to the representative household of an additional dollar in profits received during period t, w_t is the real wage paid to the worker, q_t^k is the remuneration rate for each unit of capital k_t, and g_t is the real cost of hiring (defined below), which is taken as given by the firm. As in Gertler and Trigari (2009) and Blanchard and Gali (2010), the cost of hiring is a function of labour market tightness x_t, such that $g_t = Bx_t^{\alpha}$, where α is the elasticity of labour market tightness with respect to hiring costs such that $\alpha \geq 0$; and B is a scale parameter such that $B \geq 0$.

Thus the firm chooses $\{k_t, n_t, v_t\}_{t=0}^{\infty}$ to maximize equation (24) subject to equations (20) and (21). By substituting equation (21) into equation (24) and letting ξ_t denote the non-negative Lagrange multiplier on equation (20), the first-order conditions are

$$q_t^k = \theta y_t / k_t \tag{25}$$

$$w_t = (1-\theta) y_t / n_t - \xi_t + (1-\delta_n)\, \beta E_t(\lambda_{t+1}/\lambda_t)\xi_{t+1}, \tag{26}$$

$$g_t = q\,(x_t)\,\xi_t. \tag{27}$$

Equation (25) imposes that the rate of capital remuneration, q_t^k, equals the marginal product of capital in each period t, $\theta y_t / k_t$. Equation (26) equates the real wage, w_t, to the marginal rate of transformation. The marginal rate of transformation depends on the marginal product of labour, $(1-\theta) y_t / n_t$, but also, due to the presence of labour market frictions, on present and future foregone costs of hiring. The latter two components are the shadow value of hiring an additional worker, ξ_t, net of the savings in hiring costs resulting from the reduced hiring needs in period $t+1$ if the job survives job destruction, $(1-\delta_n)\, \beta E_t(\lambda_{t+1}/\lambda_t)\xi_{t+1}$. In a model without labour market search only the marginal product of labour appears. Finally, equation (27) states that the cost of posting an additional vacancy, g_t, equals the expected benefits that the additional hiring takes into production, $q\,(x_t)\,\xi_t$.

3.2 Households

There exists a representative household. A fraction n_t of its members are employed. The remaining members are unemployed and searching for jobs. All members pool their resources so as to ensure equal consumption. The household maximizes utility from consumption,

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln(c_t) - \chi n_t^{1+\phi}/(1+\phi) \right], \tag{28}$$

subject to the following period budget constraint,

$$w_t n_t + k_t q_t^k + f_t + \tau_t = c_t + i_t, \tag{29}$$

where $w_t n_t$ is the remuneration of labour, $k_t q_t^k$ is the remuneration from renting k_t units of capital at the rate q_t^k, f_t are real profits reverted from the firm sector to households in a lump-sum manner, τ_t are real lump-sum transfers from the government and i_t are the units of output invested. By investing i_t units of output during period t, the household increases the capital stock k_{t+1} available during period $t+1$ according to

$$k_{t+1} = (1-\delta_k)k_t + i_t, \tag{30}$$

where the depreciation rate satisfies $0 < \delta_k < 1$. Thus the household chooses $\{c_t, k_{t+1}, i_t\}_{t=0}^{\infty}$ to maximize its utility (28) subject to the evolution of capital stock (30) and the budget constraint (29) for all $t = 0, 1, 2, ...$ Substituting equation (30) into (29) for i_t and letting λ_t denote the non-negative Lagrange multiplier on the resulting equation, the first-order conditions are

$$\lambda_t = 1/c_t, \tag{31}$$

and

$$\lambda_t = \beta E_t \lambda_{t+1}[q_t^k + (1-\delta_k)]. \tag{32}$$

According to equation (31), the Lagrange multiplier equals the household's marginal utility

of consumption. Equation (32) is the standard Euler equation for capital, which links the intertemporal marginal utility of consumption with the real remuneration of capital.

3.3 The labour market and wage bargaining

The structure of the model guarantees that a realized job match yields some pure economic surplus. The split of this surplus between the worker and the firm is determined by the wage level, which is set according to the Nash bargaining solution. That is, the firm and worker each receive a constant fraction of the joint match surplus, which is the sum of firm and worker surplus. The worker surplus, $\mathcal{S}_t^h$, is given by the wage, w_t, minus the worker's opportunity cost of holding a job, $\overline{w}_t$, plus the expected surplus in the next period $t+1$ if the match survives separation, which yields

$$\mathcal{S}_t^h = w_t - \overline{w}_t + (1-\delta_n)\beta E_t \frac{\lambda_{t+1}}{\lambda_t}\mathcal{S}_{t+1}^h, \tag{33}$$

where $\overline{w}_t = (\chi n_t^{\phi})/\lambda_t$ (i.e. the worker's opportunity cost of holding a job comprises the labour disutility). The Lagrange multiplier ξ_t represents the firm surplus of an additional worker (i.e. $\mathcal{S}_t^f \equiv \xi_t$). Hence, if we solve equation (26) with respect to ξ_t, the firm surplus, $\mathcal{S}_t^f$, is given by the marginal product of labour, minus the wage, plus the expected surplus in the next period $t+1$ if the match survives separation, which yields

$$\mathcal{S}_t^f = (1-\theta)y_t/n_t - w_t + (1-\delta_n)\beta E_t \frac{\lambda_{t+1}}{\lambda_t}\mathcal{S}_{t+1}^f. \tag{34}$$

The total surplus from a match is the sum of the worker's and firm's surpluses, $\mathcal{S}_t^h + \mathcal{S}_t^f$. Let η denote the household's bargaining power. Nash bargaining implies that the household receives a fraction η of the total match surplus:

$$\mathcal{S}_t^h = \eta(\mathcal{S}_t^h + \mathcal{S}_t^f). \tag{35}$$

Combining equations (33)-(35) and using the first-order condition for vacancies, equation

(27), to derive $\mathcal{S}_{t+1}^{f} = g_{t+1}/q(x_{t+1})$, we can write the agreed wage as:

$$w_t = \eta\left[(1-\theta)y_t/n_t + \beta E_t\left(\lambda_{t+1}/\lambda_t\right)g_{t+1}\right] + (1-\eta)(\chi n_t^{\phi})/\lambda_t. \tag{36}$$

Equation (36) shows that the wage comprises two components. First, for a fraction η, the marginal product of labour plus a reward from saving in hiring costs in period $t+1$. Second, for a fraction $1-\eta$, the worker's opportunity cost of holding a job.

3.4 Model solution and estimation

In order to produce a quantitative assessment of the system we need to parameterize the matching function. Following Petrongolo and Pissarides (2001), we use the standard Cobb-Douglas function

$$m_t = \overline{\mu} u_t^{\mu} v_t^{1-\mu}, \tag{37}$$

where $\overline{\mu}$ is a scaling factor and μ is the elasticity of the matching function with respect to unemployment.

We can now describe the solution of the system. Combining the firm's profit conditions (24), the household's budget constraint (29) and assuming that the government balances the budget with lump-sum transfers produces the aggregate resource constraint

$$y_t = c_t + i_t + v_t g_t. \tag{38}$$

Substituting the remuneration of capital q_t^k from equation (25) into equation (32), accounting for equations (20)-(22), (26), (27), (30), (31), (36), (38), (37), and the definitions of n_t, x_t, $p\left(x_t\right)$, $q\left(x_t\right)$ and g_t the model describes the behaviour of the 16 endogenous variables $\{y_t, c_t, i_t, \lambda_t, \xi_t, n_t, k_t, u_t, v_t, m_t, p\left(x_t\right), q\left(x_t\right), g_t, x_t, w_t, a_t\}$, and the persistent autoregressive processes of the exogenous shocks $\{\varepsilon_{at}, \varepsilon_{\psi t}\}$. The equilibrium conditions do not have an analytical solution. Consequently, the system is approximated by loglinearizing its equations around the stationary steady state. In this way, a linear dynamic system describes the path of the endogenous variables' relative deviations from their steady-state value, accounting for

the exogenous shocks. The solution to this system is derived using Klein (2000).

We estimate the model's structural parameters by using a minimum distance estimator, as in Christiano, Eichenbaum and Evans (2005).[7] Specifically, the parameters are chosen so that the impulse responses to the news shock of a set of endogenous variables in the theoretical model match as closely as possible the responses estimated from the VAR. The state-space representation of the model can be expressed as:

$$\mathcal{X}_t = \Phi(\iota)\mathcal{X}_{t-1} + \Omega(\iota)\varepsilon_t \tag{39}$$

$$\mathcal{Y}_t = \Xi(\iota)\,\mathcal{X}_t \tag{40}$$

where equation (40) describes the evolution of the state vector, $\mathcal{X}_t$, equation (39) relates the vector of the observable variables, $\mathcal{Y}_t$, with the states of the economy, and ε_t denotes the vector of the structural errors, which are normally distributed with zero mean and $I_{d\varepsilon}$ covariance matrix. Finally, the elements of the matrices $\Xi(\iota)$, $\Phi(\iota)$ and $\Omega(\iota)$ are non-linear functions of the structural parameter vector ι.

Equations (39) and (40) can be used to analyze the effects of the shocks disturbing the economy, in other words, to study agents' optimal responses to small structural shocks. Such information is summarized by the following $(m \times dy \times d\varepsilon) \times 1$ vector valued function, which represents the impulse response function (IRF):

$$R(m;\iota) \equiv \left(vec\left(\frac{\partial \mathcal{Y}_{t+1}}{\partial \varepsilon_t}\right)', ..., vec\left(\frac{\partial \mathcal{Y}_{t+m}}{\partial \varepsilon_t}\right)'\right)' = \left(\Omega(\iota)' \otimes \Xi(\iota) \otimes I_m\right) b(m;\iota), \tag{41}$$

where $b(m;\iota) \equiv \left(vec\left[\Phi(\iota)\right]', ..., vec\left[\Phi(\iota)^m\right]'\right)'$, m denotes the number of impulse-response periods, dy and $d\varepsilon$ represent the dimension of $\mathcal{Y}_t$ and ε_t respectively, the vec operator transforms a matrix with dimensions $dy \times d\varepsilon$ to a $(dy \times d\varepsilon) \times 1$ vector by stacking the columns and the symbol $\otimes$ represents the Kronecker product operator.

Using the moving average representation of the empirical model in equation (7) and the

[7] Theodoridis (2011) provides a detailed assessment of this methodology.

identification scheme discussed in the previous section we can obtain the IRF in the data:

$$R\left(m;\Theta,\tilde{A},\gamma^{*}\right)\equiv\left(vec\left(\frac{\partial\mathcal{Y}_{t+1}}{\partial\varepsilon_{t}}\right)',...,vec\left(\frac{\partial\mathcal{Y}_{t+m}}{\partial\varepsilon_{t}}\right)'\right)'=\left(\left(\tilde{A},\gamma^{*}\right)'\otimes I_{m}\right)b\left(m;\Theta\right), \quad (42)$$

where $b\left(m;\Theta\right)\equiv\left(vec\left(B_{1}\right)',...,vec\left(B_{m}\right)'\right)'$. For any positive definite weighting matrix W, an estimate of the structural parameter vector ι can be obtained by solving the following minimization problem

$$\widehat{\iota}=\arg\min\mathcal{M}, \quad (43)$$

where

$$\mathcal{M}=\left(R\left(m;\iota\right)-R\left(m;\Theta,\tilde{A},\gamma^{*}\right)\right)'W\left(R\left(m;\iota\right)-R\left(m;\Theta,\tilde{A},\gamma^{*}\right)\right). \quad (44)$$

In the estimation of the theoretical model the IRF $R\left(m;\Theta,\tilde{A},\gamma^{*}\right)$ corresponds to the mean of the posterior distribution. To make sure the results are robust to the choice of the weighting matrix, we assume that W is either an identity matrix, which assigns equal weights, or it is the inverse of the diagonal matrix of the posterior variance of $R\left(m;\Theta,\tilde{A},\gamma^{*}\right)$, which assigns variance weights. In what follows we report results from the variance weights, since the findings are very similar across specifications. The estimated value of each parameter and the associated standard error are described below and reported in the first column of Table 1.

The quarterly discount factor β is estimated equal to 0.995, which pins down a real interest rate equal to approximately 2 percent, a value commonly used in the literature. Consistent with US data, as in Shimer (2012), the value of the exogenous job separation rate, δ_n, is estimated equal to 8 percent and the value of the capital destruction rate, δ_k, is estimated equal to 2.2 percent, similar to King and Rebelo (1999). The parameter of the production capital share, θ, is estimated equal to 0.40, in line with studies such as Ireland (2004) and King and Rebelo (1999). The estimate of the parameter B determines the steady-state share of hiring costs over total output, vg/y. The estimated value of B is equal to 0.031, implying that hiring costs represent one-tenth of a percentage point (0.001) of total output, in line with Gali (2010).

The household's bargaining power, η, is estimated equal to 0.4, close to the value of 0.5 commonly used in the literature. In order to satisfy the Hosios condition, which ensures that the equilibrium of the decentralized economy is Pareto efficient, we impose that the relative bargaining power of the worker, $\eta/(1-\eta)$, is equal to the elasticity of labour market tightness with respect to hiring costs, α, that is $\eta/(1-\eta) = \alpha$.[8] This implies that the elasticity of labour market tightness with respect to hiring costs, α, is equal to 0.66, which is similar to the value in Blanchard and Gali (2010). The inverse of the Frisch intertemporal elasticity of substitution in labour supply, ϕ, is estimated equal to 0.50, which is in between the micro- and macro-evidence as detailed in Card (1994) and King and Rebelo (1999). In line with Blanchard and Gali (2010), the estimate of the disutility of labour, χ, is equal to 1. The elasticity of the matching function with respect to unemployment, μ, is estimated equal to 0.60, close to the value of 0.5 commonly used in the literature. The autoregressive coefficients of the neutral technological and news processes, ρ_a and ρ_ψ, are estimated equal to 0.99 and 0.91, in line with King and Rebelo (1999) and Barsky and Sims (2011). The standard deviation of the news process, σ_ψ, is estimated equal to 0.04. Similarly to Christiano, Motto and Rostagno (2010), the standard deviation of the neutral technological process, σ_a, is constrained to be equal to $\sigma_\psi/(1-\rho_\psi)$, since it would be problematic to estimate this parameter without identifying the variables' impulse responses to the neutral technology shock. Finally, we calibrate the remaining scaling parameters as follows. The scaling parameter in the matching function, $\overline{\mu}$, is set equal to 0.43, which ensures that the steady-state probability of filling a vacancy is equal to 0.9, as in the data. The steady-state value of the neutral technological process, a, is conveniently set equal to 1, as it does not affect the dynamics of the system.

4 News shocks in the theoretical model

In this section, we investigate to what extent the theoretical model is able to replicate the identified news shocks in the data and reproduce standard business cycle statistics. We also focus on the role of the job destruction rate and real wage rigidities for the model's dynamics.

[8] Hosios (1990) and Thomas (2011) provide a formal derivation and further analysis on this condition.

Figure 8 reports the response of selected variables to a one percent standard deviation news shock from the theoretical model (dashed line) against the estimates from the empirical model (solid line). Each plot also reports the 16-84 percent confidence interval from the VAR model (shadowed area). In response to a positive news shock the firm anticipates that the surplus from establishing a match increases, thereby leading to an increase in vacancy posting that generates a decrease in unemployment. High vacancy posting and low unemployment raise labour market tightness, thereby increasing the job finding rate. In the theoretical model output does not react to the news shock on impact, in contrast to the observed data, since both inputs of production are state variables which are fixed at the beginning of the period. Higher consumption and stable output lead to a fall in investment. The figure shows that the theoretical model closely replicates the estimated reaction of observed variables to the identified news shock, as all the theoretical responses, with the exception of unemployment, wages and investment, lie in the confidence intervals of the VAR model over the sample period. The opposite reactions of output and consumption suggest that the focus on the variables' positive comovements during the anticipation period of the news shock is somehow misplaced, a conclusion shared by a number of recent studies, such as Leeper and Walker (2011) and Barsky and Sims (2011). In addition, similarly to Den Haan and Kaltenbrunner (2009), the analysis shows that positive comovements in the variables materialize once the news shock realizes, rather than during the anticipation period.

To evaluate the model's performance Table 2 reports the standard business cycle statistics for the model and the data. It reports statistics conditional on both shocks (column 2) and on either unanticipated technology shocks (column 3) or anticipated news shocks (column 4). When we condition the model on technology shocks, as in column 3 in the table, the model matches the statistics in the data relatively well. In particular, it accurately captures the sign of the variables' comovements with output, as all the variables, except unemployment, have a positive correlation with output. However, the theoretical framework fails to reproduce a few important statistics. First, consumption is more volatile than in the data, since its relative volatility with respect to output is 0.66 in the model, compared to 0.53 in the data. Second, unemployment and the job finding rate are substantially less volatile than in the data, since

their relative volatility with respect to output is equal to 0.83 and 2.65 respectively in the model, while their values in the data are 1.43 and 4.93 respectively. These shortcomings are typical of standard search and matching models, as detailed in Shimer (2005), and one way to address them is to enrich the model with habit in consumption, as shown in Di Pace and Faccini (2012). When we condition the model on news shocks, as in column 4 in Table 2, the variables' statistics are substantially similar to those generated by technology shocks. This echoes the findings in Karnizova (2010) and Den Haan and Kaltenbrunner (2009), who also establish that business cycle statistics conditional on either technology shocks or news shocks are broadly similar since news shocks are TFP shocks that materialize in the future, they quickly inherit the properties of realized TFP shocks. Finally, column 2 in Table 2 reports the business cycle statistics of the model under both shocks. As expected, the business cycle statistics generated by both shocks are broadly similar to those generated by the two shocks separately, suggesting that the contribution of news shocks to business cycle fluctuations is limited.

Overall the analysis shows that a simple general equilibrium model of the business cycle is able to capture fairly well the variables' responses to news shocks in the data, except for the reaction of unemployment and wages. Hence, the next step is to investigate to what extent refinements to the basic framework improve the model's performance. In particular, we focus on the role of the job destruction rate and real wage rigidities.

Figure 8 shows that the reaction of unemployment to the news shock is outside the VAR model's confidence bands after four quarters, suggesting that the unemployment response is too persistent in the model. In the theoretical framework equations (20) and the definition of unemployment (i.e. $u_t = 1 - n_t$) imply that unemployment depends on the job finding rate, which is endogenous and relies on the matching technology, and on the job destruction rate, which is exogenous. Hence, a natural extension is to evaluate to what extent the job destruction rate is important for the dynamics of unemployment in the context of a news shock. Figure 9 shows the reaction of the variables for different values of the job destruction rate. The associated parameter estimates are reported in columns (2) and (3) of Table 1. It clearly emerges that the job destruction rate has non-trivial effects on unemployment, since

the response of this variable substantially changes for different values of δ_n. For instance, when δ_n is set equal to 0.02, the response of unemployment is closer to its counterpart in the data and lies inside the confidence bands of the VAR model. We use the metric in equation (44) to evaluate which model specification delivers impulse response functions closer to the VAR model. A high value of the metric $\mathcal{M}$ indicates that the impulse responses in the theoretical model are on average different from those in the VAR model. The last row in Table 1 shows that for the alternative values of δ_n equal to 0.02 and 0.14 the associated metrics estimates are 85 and 206 respectively. Hence for δ_n equal to 0.02 the model delivers variables' responses closer to the VAR estimates, since the associated metric is lower than the value of 169 in the benchmark specification. However, although this alternative specification delivers accurate responses to the news shock, the associated steady state is implausible, since it implies a steady-state unemployment rate of 16 percent. Nonetheless, this analysis shows that the response of unemployment to the news shock is sensitive to the value of the job destruction rate, suggesting that enriching the theoretical model to account for an endogenous job destruction rate would certainly be a useful extension for future research.

Recent studies by Shimer (2005) and Gertler and Trigari (2009) suggest that real wage rigidities substantially affect the model's performance and improve the response of wages and unemployment in response to technology shocks. To establish to what extent this refinement to the model leads to a more accurate response of wages and unemployment to the news shock we embed real wage rigidities in the model. Following Hall (2005), real wage rigidities are accomplished by the wage norm

$$w_t^{norm} = (1 - \gamma_\omega) w_t + \gamma_\omega w_{t-1}, \tag{45}$$

where w_t^{norm} is the wage norm, and the parameter $0 < \gamma_\omega < 1$ controls for the degree of real wage rigidities. For instance, when $\gamma_\omega = 0$, the wage norm coincides with the wage bargained in period t, whereas if $\gamma_\omega = 1$, the wage norm coincides with the wage bargained in period $t-1$. Figure 10 shows the variables' responses to a news shock in the estimated model with real wage rigidities. The associated parameter estimates are reported in column

(4) of Table 1. The estimate of the wage norm parameter γ_ω is equal to 0.99, suggesting that the data prefer a high degree of sluggishness in real wages. The figure shows that real wage rigidities improve the performance of the model in replicating the response of wages and unemployment, whose reaction lies inside the VAR confidence bands. The last row of Table 1 reports the metric $\mathcal{M}$ in equation (44), whose value equal to 61 reveals that real wage rigidities deliver average responses to a news shock that are closer to the VAR model than the benchmark specification. Hence, embedding real wage rigidities would further improve the performance of the theoretical model to replicate the variables' responses to news shocks in the data.

5 Conclusion

This paper has investigated the effect of news shocks on labour market variables. News shocks are identified in the data using alternative identification strategies applied on a VAR model estimated with Bayesian methods. The identification schemes assume that a news shock explains most of the movements in future productivity but has no impact on current productivity. The results show that in the aftermath of the news shock, unemployment falls, whereas wages and the job finding probability increase. In addition, the inclusion of labour market variables confirms that output and investment modestly fall and consumption increases in reaction to a news shock, in line with recent studies that abstract from labour market dynamics. The VAR model also reveals that despite news shocks being important in explaining fluctuations in labour market variables at different time horizons, they have a limited effect on movements in real activity. In addition, historically news shocks are important for the dynamics of the job finding rate and unemployment, but they have a limited role in explaining fluctuations in wages.

We use the results from the empirical analysis to study implications for macroeconomic modelling. We find that a fairly standard search and matching model of the labour market is able to replicate the reaction of macroeconomic variables to news shocks fairly well. We establish that the job destruction rate and real wage rigidities are important to replicate the

response of unemployment and wages to news shocks in the data and enhance the overall variables' responses in the model.

This paper puts forward a few valuable extensions for future research. First, the analysis shows that the job destruction rate plays a non-trivial role in the response of unemployment to the news shock. It would therefore be interesting to extend the model to include endogenous job destruction, although this would substantially complicate the theoretical framework. However, endogenous job destruction may prove important, since the anticipation effect in reaction to news shocks may induce sharp movements in the rate at which jobs are destroyed, thereby potentially affecting movements in unemployment and output. Second, the analysis shows that real wage rigidities included by a simple wage norm are important for the dynamics of labour market variables. It would certainly be interesting to investigate whether a more sophisticated wage setting mechanism derived from first principles, as in Gertler and Trigari (2009), is able to further improve the variables' responses to the news shock. Finally, the empirical analysis could be extended to identify TFP shocks in conjunction with news shocks, which would enable the estimation of the standard deviation of technology σ_a in the theoretical model. These investigations remain open for future research.

6 Appendix. The data

This appendix describes the data used in the estimation of the VAR model. The data are quarterly, seasonally adjusted, and cover the period 1960:Q1-2007:Q1. The series used in the estimation are: total factor productivity (TFP), non-durables and services consumption, real output per capita, the unemployment rate, wages per person and the job finding rate. The TFP variable is a quarterly version of the series constructed by Basu et al. (2006), who correct the traditional Solow residual by removing its demand component that corresponds to the utilization of capital and the labour effort. Output is measured in log terms of the real output in the non-farm business sector and the consumption variable is defined as the log of real non-durables and services from FRED. The unemployment rate (age 16 years and over) is from FRED, the series of wages per person (defined as the product of the compensation in

the non-farm business times the real output in the non-farm business divided by the nominal output and employment in the non-farm business sector) and the job finding rate are from Shimer (2012). The series for TFP, consumption, output and wages are detrended using the Hodrick-Prescott filter, whereas the series for unemployment rate and the job finding rate are de-meaned. To ensure results are robust to the filtering procedure, we have estimated the model detrending the data using a linear trend and found that the results continue to hold. An Appendix which details the robustness of the results is available upon request from the authors.

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Table 1: DSGE Parameter Estimates

	(1)			**(2)**			**(3)**			**(4)**		
	Mode	5%	95%	*Mode*	5%	95%	*Mode*	5%	95%	*Mode*	5%	95%
β	0.99	0.99	1.00	0.99	0.98	0.99	0.99	0.98	0.99	0.98	0.98	1.00
δ_n	0.08	0.08	0.08	0.02	0.20	0.20	0.02	0.20	0.20	0.08	0.08	0.10
δ_k	0.02	0.02	0.03	0.02	0.02	0.03	0.02	0.02	0.03	0.02	0.02	0.03
θ	0.40	0.20	0.40	0.40	0.23	0.40	0.40	0.20	0.40	0.40	0.38	0.40
$\upsilon g/y$	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.01
η	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.99	0.40	0.40	0.40
ϕ	0.50	0.50	2.27	0.50	0.50	3.42	0.50	0.50	3.50	0.50	0.50	3.50
χ	1.00	1.00	2.50	1.12	1.00	2.50	1.00	1.00	2.50	1.53	1.00	2.50
μ	0.60	0.57	0.82	0.45	0.45	0.70	0.70	0.45	0.70	0.45	0.45	0.70
ρ_a	0.91	0.90	0.91	0.94	0.97	1.00	0.90	0.09	1.00	0.94	0.99	1.00
ρ_ψ	0.91	0.00	0.97	0.94	0.02	0.99	0.90	0.00	0.99	0.94	0.00	1.00
σ_ψ	0.04	0.03	0.07	0.03	0.00	0.02	0.05	0.00	0.06	0.02	0.00	5.00
σ_a	0.42	0.35	0.68	0.49	0.01	0.56	0.47	0.00	0.80	0.32	0.00	1.53
γ_w										0.99	0.00	1.00
MDE	168.89			85.28			205.93			60.78		

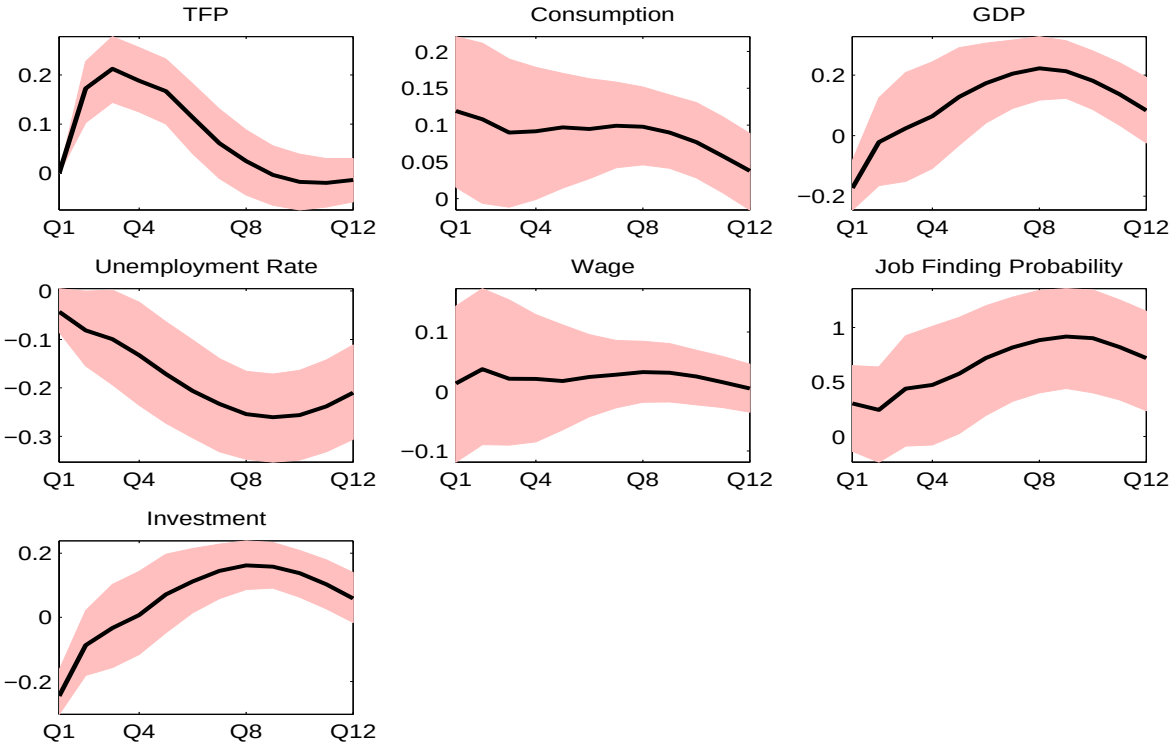
Notes: The table shows the parameters' estimates for different versions of the model. Column (1) refers to the benchmark specification. Columns (2) and (3) refer to the specification with the job destruction rate δ_n equal to 0.02 and 0.14 respectively. Column (4) refers to the specification that includes the real wage norm γ_w. The last row reports the metric $\mathcal{M}$ as defined in equation (44).

Table 2: Summary Statistics

	Data	**Both Shocks**	**TFP Shock**	**News Shock**
	(1)	**(2)**	**(3)**	**(4)**
Relative Standard Deviations				
σ_a/σ_y	0.59	0.50	0.52	0.46
σ_c/σ_y	0.53	0.70	0.66	0.76
σ_y/σ_y	1.00	1.00	1.00	1.00
σ_u/σ_y	1.43	0.80	0.83	0.76
σ_w/σ_y	0.52	0.57	0.54	0.60
σ_p/σ_y	4.93	2.23	2.65	1.34
Comovements				
$Corr(y_t, a_t)$	0.40	0.93	0.93	0.94
$Corr(y_t, c_t)$	0.83	0.87	0.83	0.92
$Corr(y_t, u_t)$	-0.52	-0.94	-0.94	-0.94
$Corr(y_t, w_t)$	0.45	0.96	0.95	0.97
$Corr(y_t, p_t)$	0.62	0.56	0.51	0.80
$Corr(u_t, v_t)$	-0.89	-0.52	-0.48	-0.82

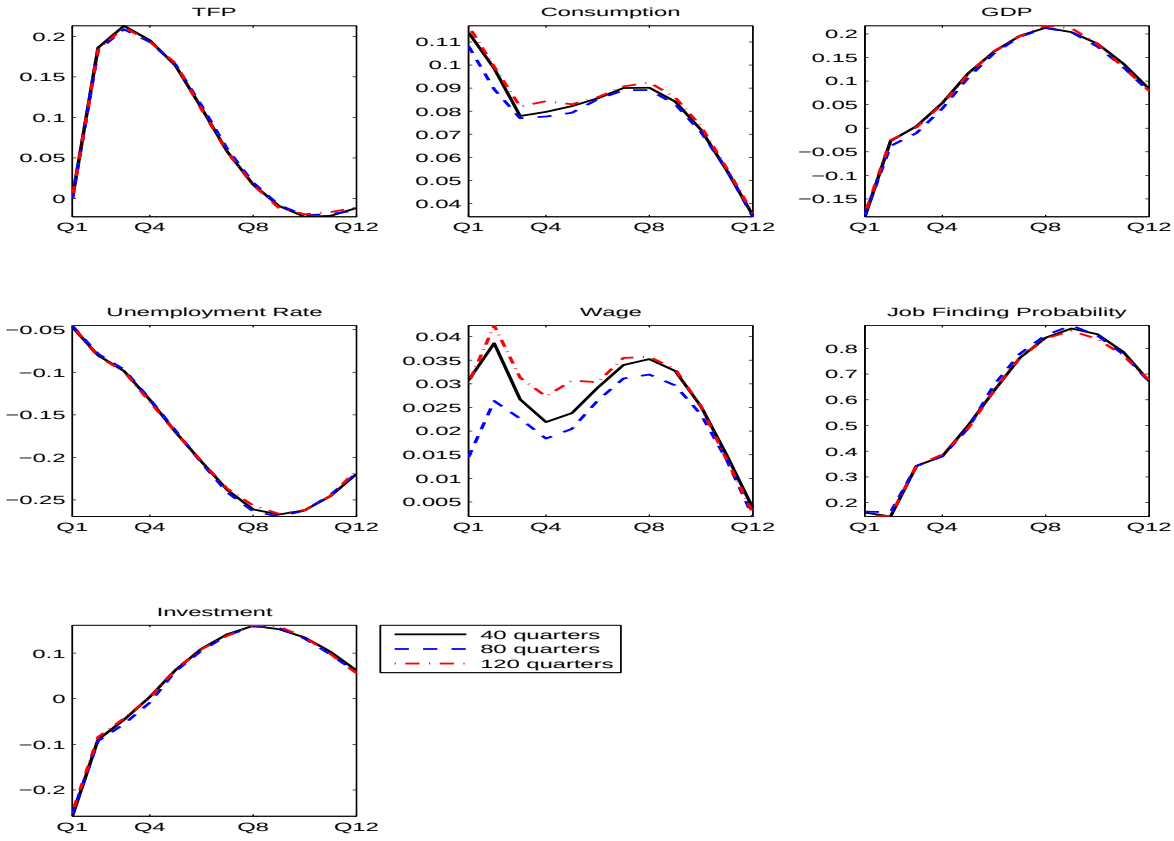
Notes: The table shows the summary statistics of selected variables in the data and in the theoretical model. Column (1) refers to the data. Column (2) refers to the benchmark specification with both technology and news shocks. Column (3) refers to the specification with technology shocks only. Column (4) refers to the specification with news shocks only.

Figure 1: VAR Responses to a News Shock



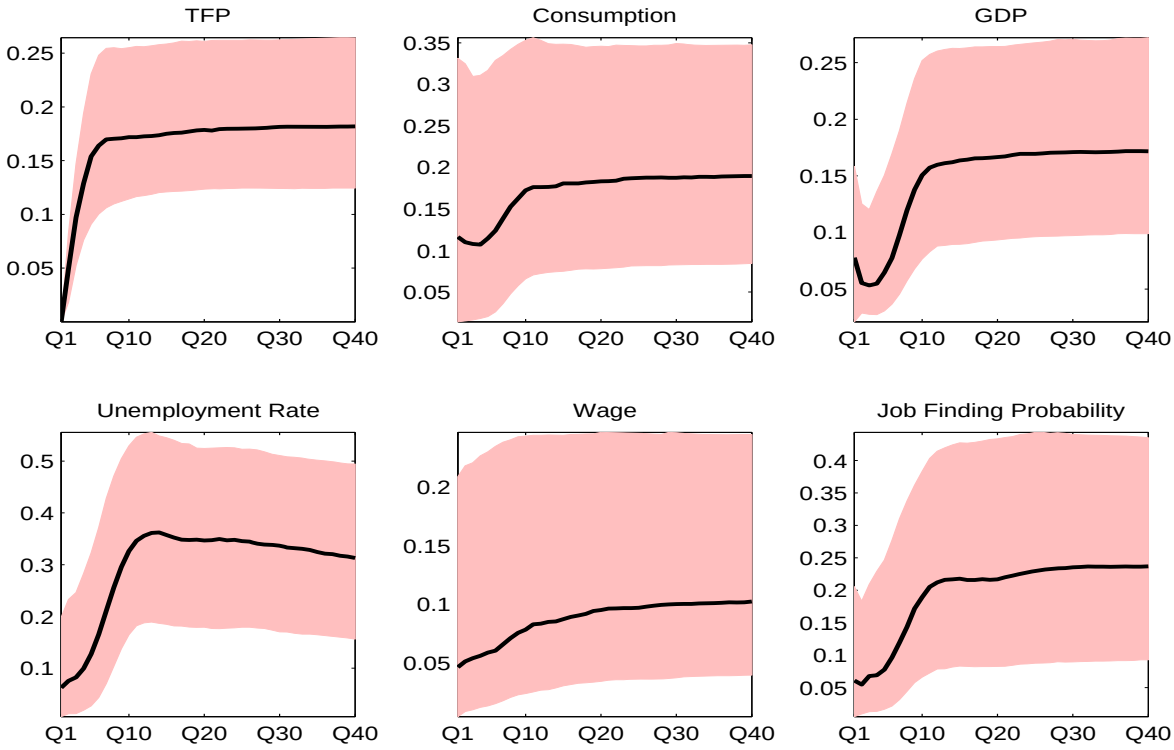
Notes: Each entry shows the response of one of the VAR model's variables to a one-percentage-deviation news shock. The solid black line reports the median responses, whereas the shadowed area reports the 16-84 percent confidence interval from the posterior distribution of the VAR model. Responses are expressed in percentage changes.

Figure 2: VAR Responses to a News Shock at Different Forecast Horizons



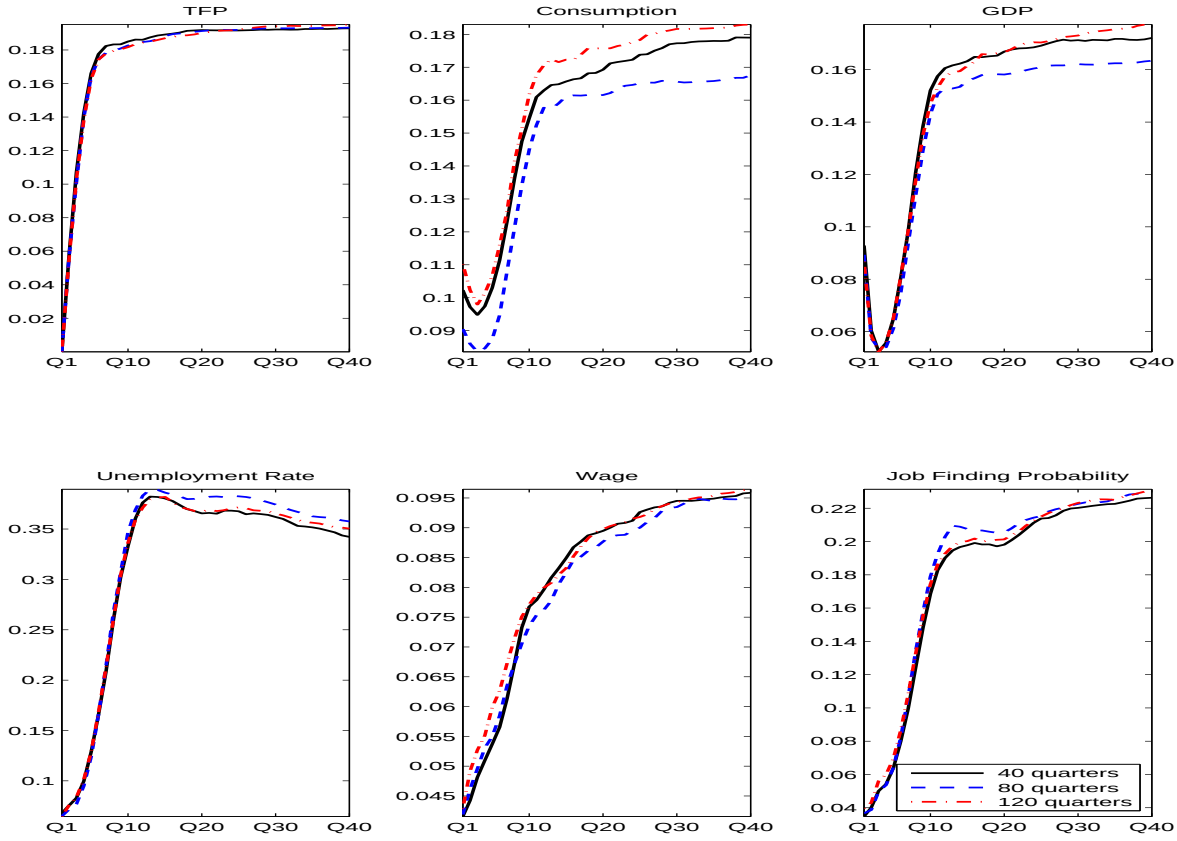
Notes: Each entry shows the response of one of the VAR model's variables to a one-percentage-deviation news shock at different forecast horizons. The solid line reports the response at 40 quarters, the dashed line reports the response at 80 quarters and the dash-dotted line reports the response at 120 quarters.

Figure 3: Contribution of News to VAR Forecast Uncertainty



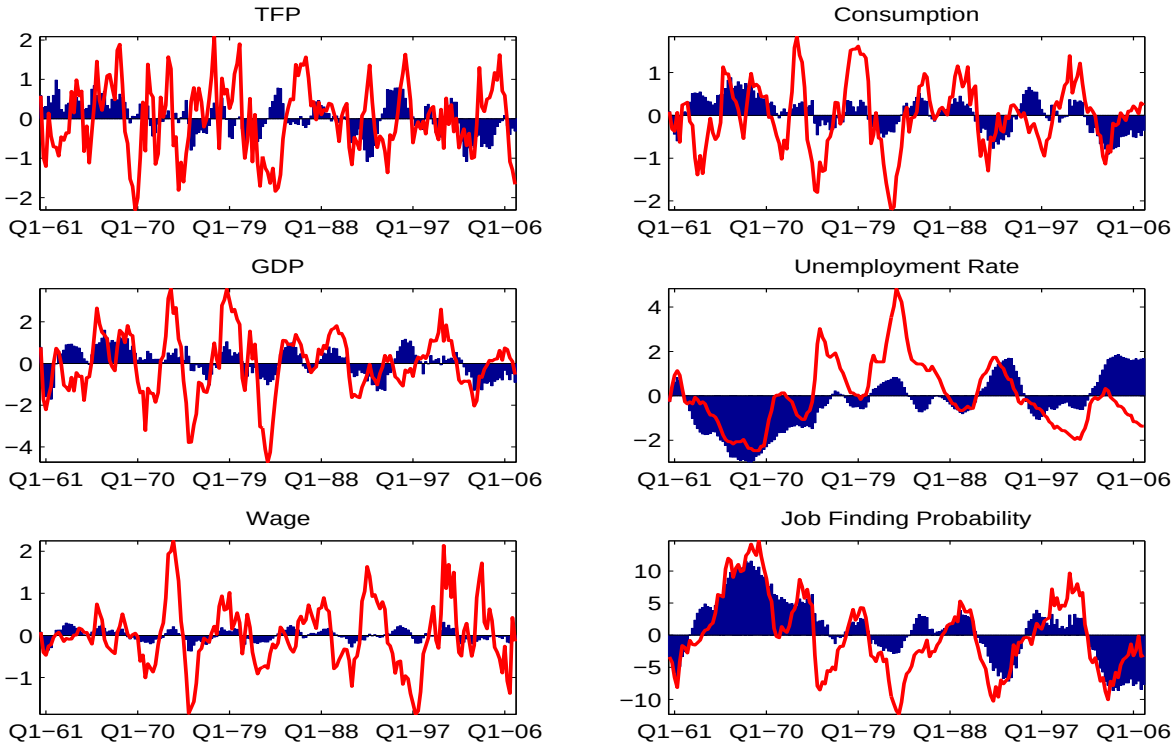
Notes: Each entry shows the fraction of the forecast error variance of the variables in the VAR model attributable to the news shock at different horizons. The shadowed area highlights the 16-84 percent confidence interval of the posterior distribution of the VAR model.

Figure 4: Contribution of News to VAR Forecast Uncertainty at Different Forecast Horizons



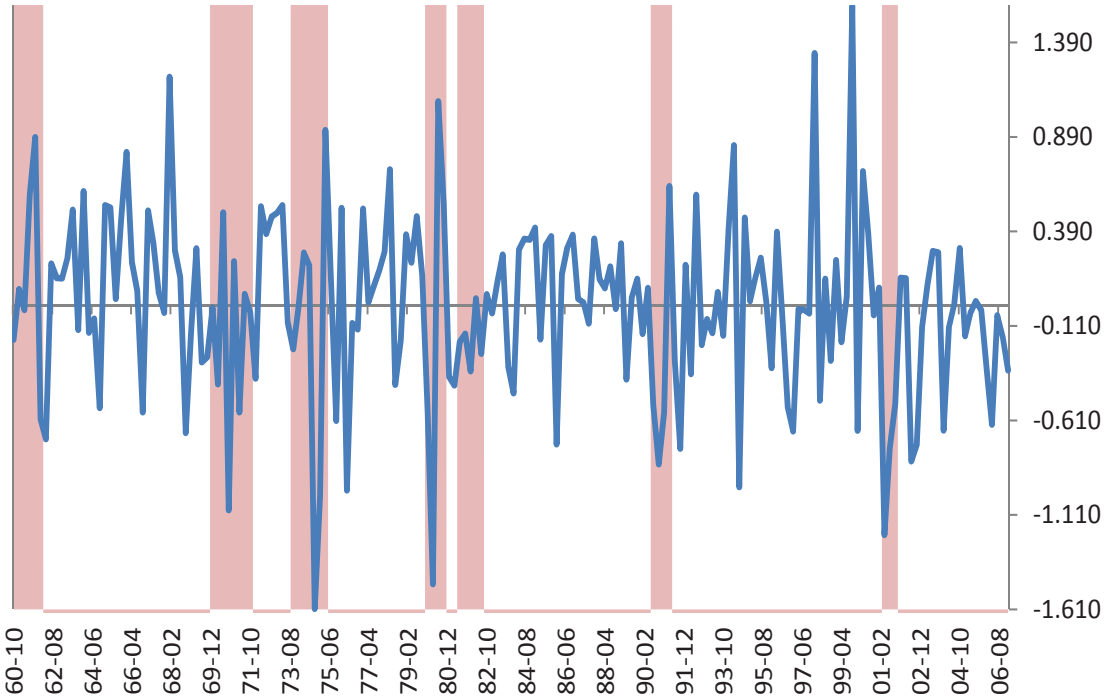
Notes: Each entry shows the fraction of the forecast error variance of the variables in the VAR model attributable to the news shock at different horizons. The solid line reports the estimate at 40 quarters, the dashed line reports the estimate at 80 quarters and the dash-dotted line reports the estimate at 120 quarters.

Figure 5: VAR Historical Decomposition



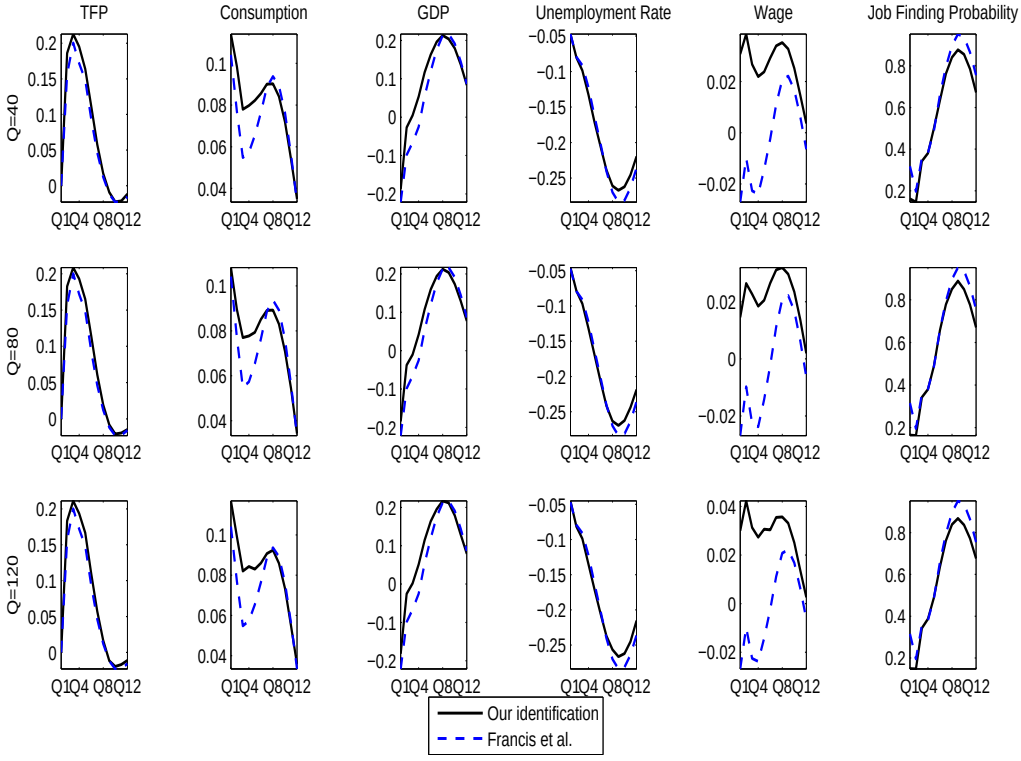
Notes: Each entry reports a variable's historical decomposition. It displays the contribution of a news shock to movements in the variables over the sample period.

Figure 6: News Shock Posterior Mean Estimates



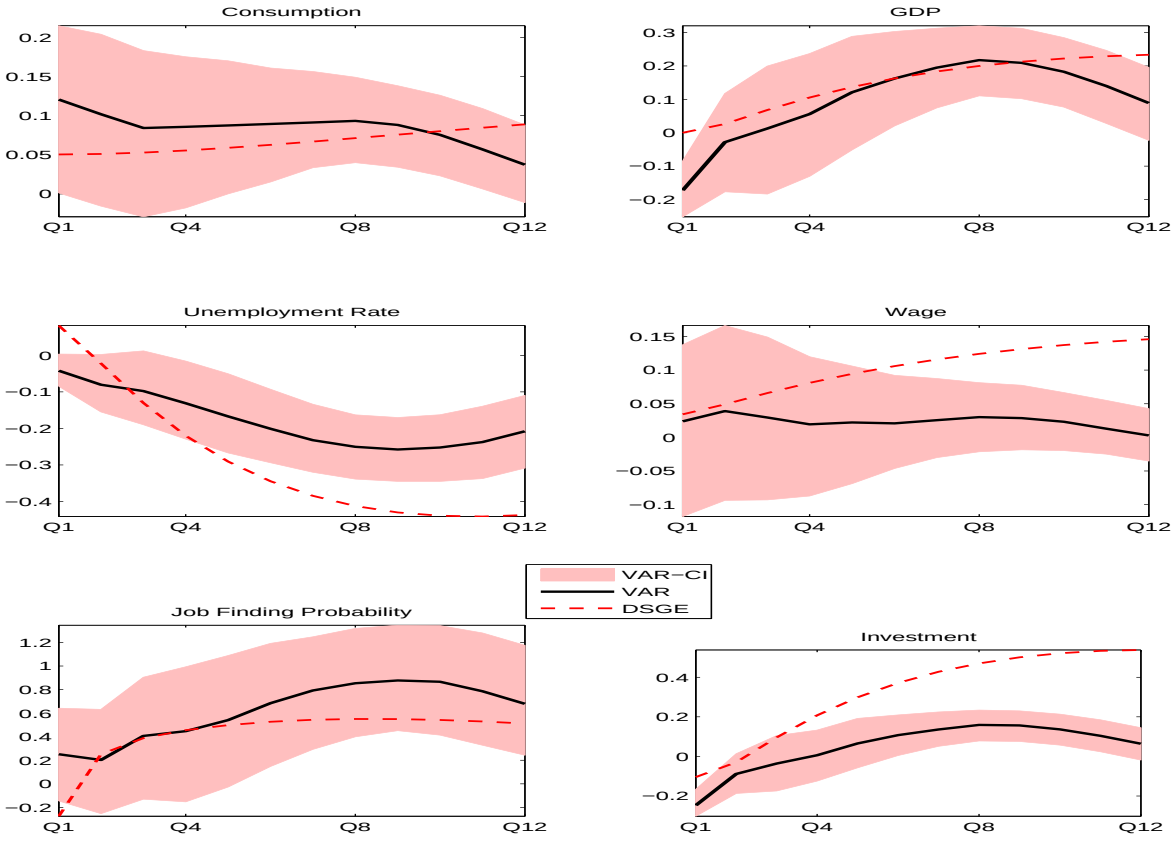
Notes: The figure shows the estimated series of the news shock from the VAR model against the recession dates as defined by the NBER business cycle dating committee.

Figure 7: VAR Responses to a News Shock for Different Identification Methods and Forecasting Horizons



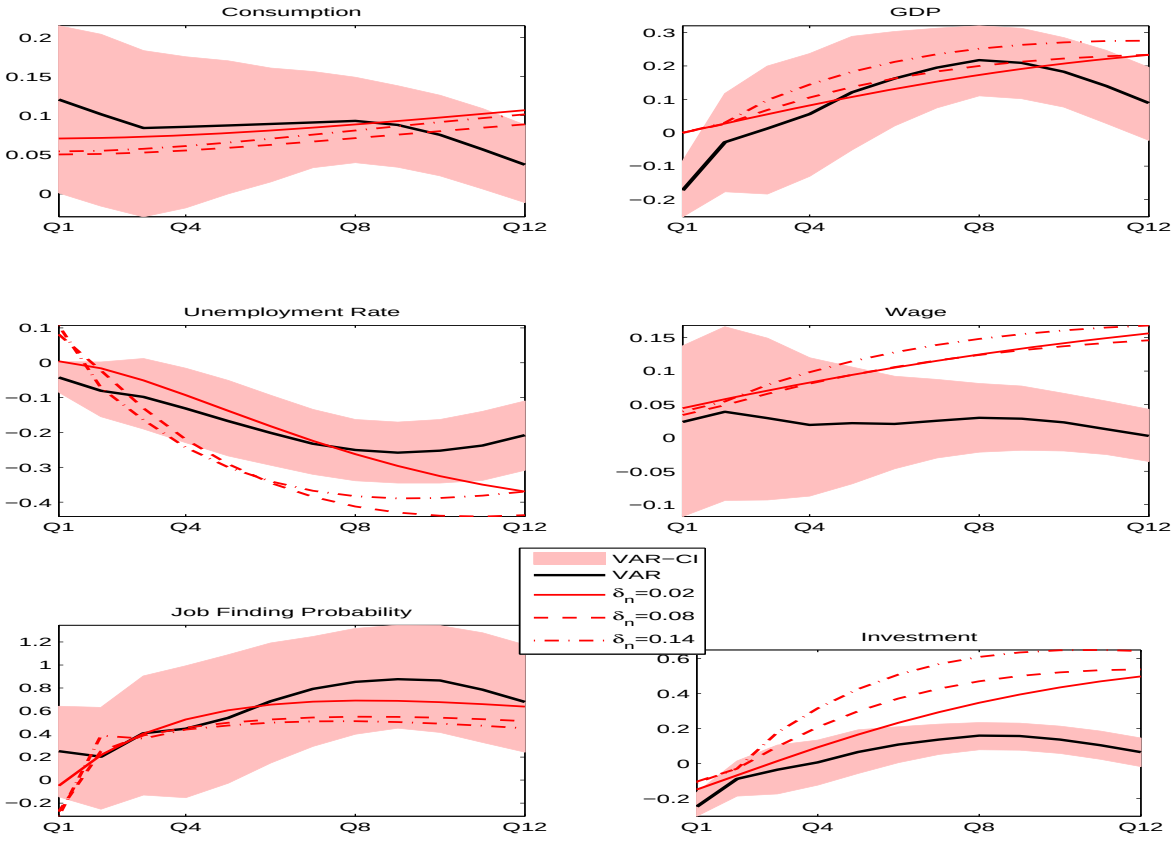
Notes: Each entry shows the response of one of the VAR model's variables to a one-percentage-deviation news shock. The solid line reports the estimates using our identification method, whereas the dashed line reports the estimates using Francis et al. (2012)'s method. The top panel shows results for $Q = 40$, so that $h = 40$ in our identification scheme and $H = 40$ in Francis et al. (2012). The middle panel shows results for $Q = 80$, so that $h = 80$ in our identification scheme and $H = 80$ in Francis et al. (2012). The bottom panel shows results for $Q = 120$, so that $h = 120$ in our identification scheme and $H = 120$ in Francis et al. (2012).

Figure 8: Theoretical Model's Impulse Response Functions to the News Shock



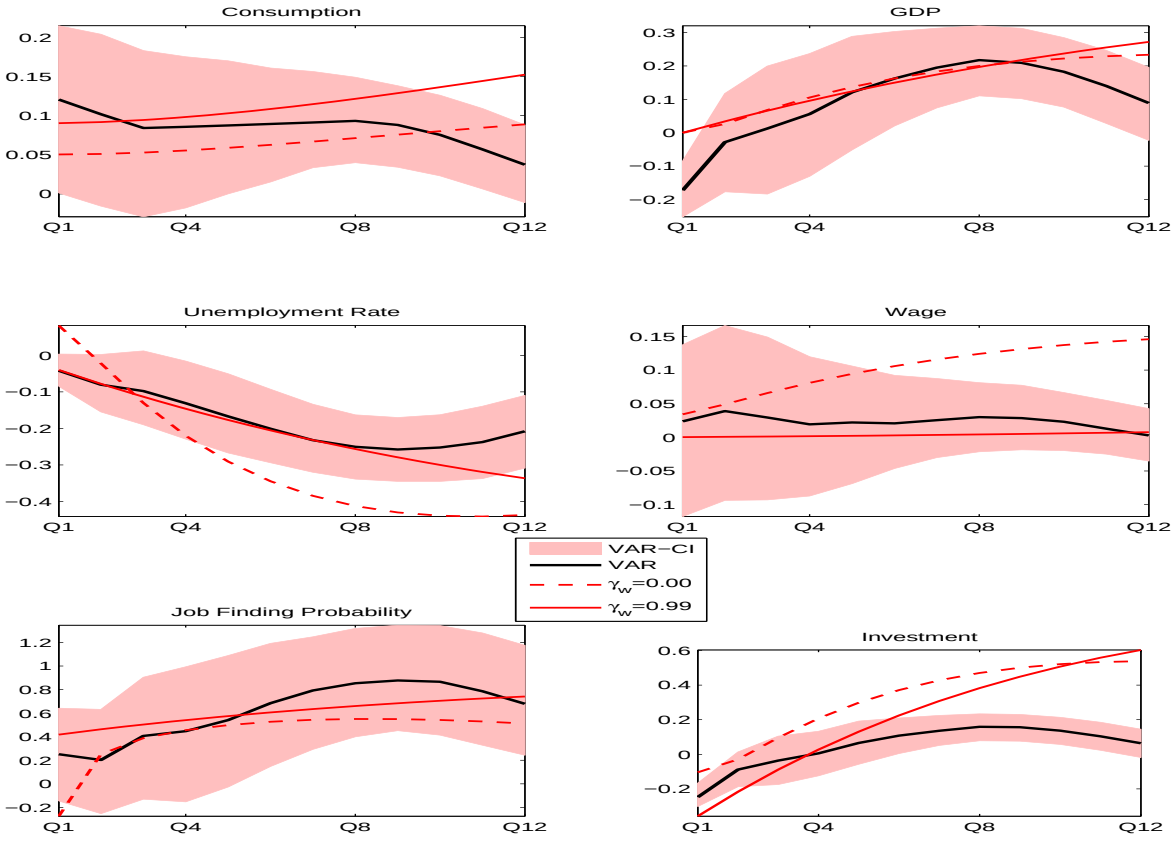
Notes: Each entry shows the percentage-point response of one of the model's variables to a one-percentage-deviation news shock. The dashed line reports the responses from the theoretical model, whereas the solid black line reports the median responses from the VAR model. The shadowed area reports the 16-84 percent confidence interval from the VAR model.

Figure 9: Sensitivity Analysis: Job Destruction Rate, δ_n



Notes: Each entry shows selected impulse responses associated with different values of the job destruction rate, δ_n. The solid black line reports the median responses from the VAR model. The shadowed area reports the 16-84 percent confidence interval from the VAR model.

Figure 10: Sensitivity Analysis: Wage Norm, γ_w



Notes: Each entry shows selected impulse responses in the presence of real wage rigidities ($\gamma_w = 0.99$) and in the benchmark model ($\gamma_w = 0$). The solid black line reports the median responses from the VAR model. The shadowed area reports the 16-84 percent confidence interval from the VAR model.