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Abstract

We enrich a baseline RBC model with search and matching frictions on the labor market and real frictions that are helpful in accounting for the response of macroeconomic aggregates to shocks. The analysis allows shocks to have an unanticipated and a news (i.e. anticipated) component. The Bayesian estimation of the model reveals that the model which includes news shocks on macroeconomic aggregates produces a remarkable fit of the data. News shocks in stationary and non-stationary TFP, investment-specific productivity and preference shocks significantly affect labor market variables and explain a sizeable fraction of macroeconomic fluctuations at medium- and long-run horizons. Historically, news shocks have played a relevant role for output, but they have had a limited influence on unemployment.

JEL Classification: E32, C32, C52.

Keywords: Anticipated productivity shocks, Bayesian SVAR methods, labor market search frictions.

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1 Introduction

A number of studies establish that anticipated changes in future disturbances, 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 labor market variables. This paper fills this gap. We enrich a baseline RBC model with search and matching frictions on the labor market and real frictions (consumption smoothing, capital utilization, investment adjustment cost), which are helpful in accounting for the response of macroeconomic aggregates to shocks. The exogenous driving forces of the model are unanticipated and news (i.e. anticipated) shocks to permanent and stationary total factor productivity (TFP), investment-specific productivity, preference, matching technology and job destruction. Using this framework, we investigate to what extent are distinct news shocks important to explain fluctuations in labor market variables and macroeconomic aggregates, and we study the propagation dynamics of relevant news shocks.

To confront the theoretical framework with the data, the model allows, but does not require, news shocks to interact with unanticipated shocks to generate aggregate fluctuations. It therefore allows both sources of exogenous disturbances to simultaneously compete to explain the data. The Bayesian estimation of the model reveals that the data prefer a version of the model that includes news shocks to stationary and non-stationary TFP, investment-specific productivity and preference shocks. Specification with labor market news only (anticipated shocks to matching technology and the job destruction rate), with all sources of news shocks, or without any source of news shocks are unsupported by the data. The analysis shows that despite the presence of labor market news shocks substantially increases the performance of the model relative to the version without news shocks. However, it diminishes the model forecast fit of output, consumption and investment when macroeconomic news shocks are present, thereby worsening the overall fit of the model.

The analysis shows that the model with macroeconomic news shocks matches the data

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

remarkably well. In addition, unanticipated shocks to stationary TFP explain the bulk of fluctuations in output, wages, vacancies and labor market tightness in the 1-quarter ahead. Subsequently, for the 1-year, 3-year and 10-year ahead horizons, news shocks to the stationary TFP become an important source of fluctuations in aggregate variables, similar to findings in Schmitt-Grohe and Uribe (2012). Historical variance decomposition shows that news shocks are a relevant source of fluctuation for consumption and output in the US postwar data whereas they play a limited role for unemployment. Finally, the model is able to identify the effect of news disturbances on labor market and macroeconomic variables. We find that the responses of macroeconomic aggregates in the anticipation phase of the news shock differ from the responses in the aftermath of the realization of the shock. For instance, in the anticipation of the news shock to the stationary TPF, the marginal product of labor rises since the expected higher productivity induces the firm to reduce labor input. Consequently, as wages increase, the firm decreases its vacancy postings, leading to a rise in unemployment that induces a fall in labor market tightness and the job-finding rate. However, once the shock realizes, employment sharply increases, reducing the marginal product of labor and, consequently, wages, whose effect is to reverse the variables' responses in the anticipation phase and mimic the standard dynamics of the unanticipated TFP shock. Similarly, the analysis shows that different dynamics during the anticipation and the realization periods are present in the other shocks.

Before proceeding with the analysis, we describe the relationship of the paper with related studies. The view that expectations generate economic fluctuations has been recently revisited in a series of influential papers by Beaudry and Portier (2004, 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 Beaudry and Portier (2006), Schmitt-Grohe 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

labor market aggregates in the context of a fully-specified general equilibrium model, with labor market search and matching frictions estimated with Bayesian methods. In contrast to the existing studies, we extend the analysis to identify the effect of news shocks on labor market aggregates, allowing for news shocks in labor market variables.

This paper also contributes to research which 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. However, they also indicate that standard real business cycle models are unable to generate positive co-movements of macroeconomic aggregates in response to news shocks, and they propose different modifications to address this shortcoming. Similarly to our paper, Den Haan and Kaltenbrunner (2009) find that labor market frictions enhance the performance of the model in matching the reactions of consumption, output and investment in response to news shocks. Our analysis substantially differs in two ways. First, it is the first study that focuses on the effect of news shocks on labor market variables, namely wages, unemployment and the job-finding rate. Second, our theoretical findings are more general as we use a baseline search and matching model, whereas these authors develop a model with endogenous labor force participation. Our analysis shows that a relatively standard model with labor market search and matching frictions is able to replicate fluctuations in 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.

The remainder of the paper proceeds as follows. Section 2 lays out the model and presents the econometric methodology and data. Section 3 presents the estimation results, comprising the empirical fit and forecasting performance of alternative models, the effect of news shocks on labor market variables and their relevance to explain historical fluctuations. Finally, Section 4 concludes.

2 The model

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

Three agents populate the model economy: 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 labor 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 labor market in detail.

2.1 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 labor force to 1, u_t also represents the unemployment rate, and $u_t \equiv 1 - n_{t-1}$. 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 labor market tightness. Notice that $p'\left(x_t\right) > 0$ and $q'\left(x_t\right) < 0$, i.e. in a tighter labor 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

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

where $q(x_t)v_t$ is the number of new matches at time t, and $\delta_{n,t}$ is the job destruction rate that follows the autoregressive process

$$\ln \delta_{n,t} = \left(1 - \rho_{\delta_n}\right) \ln \delta_n + \rho_{\delta_n} \ln \delta_{n,t-1} + \sigma_{\delta_n} \varepsilon_{\delta_n,t} + \sigma_{t+4,\delta_n} \psi_{\delta_n,t/t+4} + \sigma_{t+8,\delta_n} \psi_{\delta_n,t/t+8}, \tag{2}$$

with $0 < \rho_{\delta_n} < 1$, and where the zero-mean, serially uncorrelated innovations $\varepsilon_{\delta_n,t}$, $\psi_{\delta_n,t/t+4}$ and $\psi_{\delta_n,t/t+8}$ are normally distributed with standard deviation σ_{δ_n}, σ_{t+4,δ_n} and σ_{t+8,δ_n}. In this notation, $\varepsilon_{\delta,t}$ represents the unanticipated shock to the job destruction rate, whereas $\psi_{\delta_n,t/t+4}$ and $\psi_{\delta_n,t/t+8}$ represent the anticipated $t+4$ and $t+8$ periods ahead news shocks to the job destruction rate which bear no contemporaneous effect on the level of the job destruction rate. As shown in Theodoridis and Zanetti (2014) and Zanetti (2014), adding news shocks to the job destruction rate improves the ability of a very stylized business cycle model to replicate the unemployment dynamics and other important labor market statistics.

The firm's production function is given by

$$y_t = a_t k_t^{\theta} \left(\gamma_t n_t\right)^{1-\theta}, \tag{3}$$

where k_t and n_t denote capital and labor services, respectively, and a_t and γ_t are the stationary and non-stationary total factor of productivity (TFP) shocks. The stationary TFP shock, a_t, follows the autoregressive process

$$\ln a_t = \rho_a \ln a_{t-1} + \sigma_a \varepsilon_{a,t} + \sigma_{t+4,a} \psi_{a,t/t+4} + \sigma_{t+8,a} \psi_{a,t/t+8}, \tag{4}$$

with $0 < \rho_a < 1$ and where the zero-mean, serially uncorrelated innovations $\varepsilon_{a,t}$, $\psi_{a,t/t+4}$ and $\psi_{a,t/t+8}$ are normally distributed with standard deviation σ_a, $\sigma_{t+4,a}$ and $\sigma_{t+8,a}$. In

this notation, $\varepsilon_{a,t}$ represents the unanticipated shock to TFP, whereas $\psi_{a,t/t+4}$ and $\psi_{a,t/t+8}$ represent the anticipated $t+4$ and $t+8$ periods ahead news shocks to TFP. The growth rate of the non-stationary, labor augmented TFP shock, z_t, is stationary and follows the autoregressive process

$$\ln z_t = \ln\left(\frac{\gamma_t}{\gamma_{t-1}}\right) = (1-\rho_z)\ln z + \rho_z \ln z_{t-1} + \sigma_z \varepsilon_{z,t} + \sigma_{t+4,z}\psi_{z,t/t+4} + \sigma_{t+8,z}\psi_{z,t/t+8} \quad (5)$$

with $0 < \rho_z < 1$, and where the zero-mean, serially uncorrelated innovations $\varepsilon_{z,t}$, $\psi_{z,t/t+4}$ and $\psi_{z,t/t+8}$ are normally distributed with standard deviation σ_z, $\sigma_{t+4,z}$ and $\sigma_{t+8,z}$. In this notation, $\varepsilon_{z,t}$ represents the unanticipated shock to the growth rate of the non-stationary labor augmented TFP shock, whereas $\psi_{z,t/t+4}$ and $\psi_{z,t/t+8}$ represent the anticipated $t+4$ and $t+8$ periods ahead news shocks. Finally, capital services, k_t, depends on the utilization rate, υ_t,

$$k_t = \upsilon_t \bar{k}_{t-1}, \quad (6)$$

where $\bar{k}_{t-1}$ is the installed physical capital in period $t-1$.

2.1.1 Profit maximization

Subject to equations (1) and (3), the firm maximizes its profits,

$$E_0 \sum_{t=0}^{\infty} \beta^t \lambda_t \left[y_t - n_t w_t - k_t q_t^k - \upsilon_t g_t \right], \quad (7)$$

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 Mandelman and Zanetti (2014), the cost of hiring is a function of labor market tightness x_t, such that $g_t = B\gamma_t x_t^{\alpha}$, where α is the elasticity of labor market tightness with respect to hiring costs such that $\alpha \geq 0$ and $B \geq 0$ is a scale parameter.

Thus the firm chooses $\{k_t, n_t, \upsilon_t\}_{t=0}^{\infty}$ to maximize equation (7), subject to equations (1)

and (3). By substituting equation (3) into equation (7) and letting ξ_t denote the non-negative Lagrange multiplier on equation (1), the first-order conditions are

$$q_t^k = \theta y_t / k_t \tag{8}$$

$$w_t = (1-\theta) y_t / n_t - \xi_t + (1-\delta_{n,t})\, \beta E_t (\lambda_{t+1}/\lambda_t) \xi_{t+1}, \tag{9}$$

and

$$g_t = q\left(x_t\right) \xi_t. \tag{10}$$

Equation (8) assumes 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 (9) equates the real wage, w_t, to the marginal rate of transformation. The marginal rate of transformation depends on the marginal product of labor, $(1-\theta) y_t / n_t$, but also, due to the presence of labor 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, $(1-\delta_{n,t})\, \beta E_t (\lambda_{t+1}/\lambda_t) \xi_{t+1}$. In a model without labor market search, only the marginal product of labor appears. Finally, equation (10) states that the cost of posting an additional vacancy, g_t, equals the expected benefits that the additional hiring takes into production, $q\left(x_t\right) \xi_t$.

2.2 Households

There exists a representative household. A fraction (n_t) of its members are employed and the remaining members are unemployed, and searching for jobs. All members pool their resources to ensure equal consumption (c_t). The household utility function is:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[d_t \frac{\left(\frac{c_t}{\gamma_t} - h \frac{c_{t-1}}{\gamma_{t-1}} \right)^{1-\sigma}}{1-\sigma} - \chi \frac{n_t^{1+\phi}}{1+\phi} \right], \tag{11}$$

where d_t is a consumption preference shock that follows the autoregressive process

$$\ln d_t = \rho_d \ln d_{t-1} + \sigma_d \varepsilon_{d,t} + \sigma_{t+4,d} \psi_{d,t/t+4} + \sigma_{t+8,d} \psi_{d,t/t+8}, \tag{12}$$

with $0 < \rho_d < 1$ and where the zero-mean, serially uncorrelated innovations $\varepsilon_{d,t}$, $\psi_{d,t/t+4}$ and $\psi_{d,t/t+8}$ are normally distributed with standard deviation σ_d, $\sigma_{t+4,d}$ and $\sigma_{t+8,d}$. The parameter $0 < h < 1$ describes the degree of habit in consumption, $\sigma > 0$ is the intertemporal rate of substitution, $\phi > 0$ is the inverse of the Frisch elasticity of labor supply and $\chi > 0$ is the degree of disutility of working. The household budget constraint is

$$w_t n_t + \left[q_t^k \upsilon_t - \vartheta(\upsilon_t) \right] \bar{k}_{t-1} + f_t + \tau_t = c_t + i_t, \tag{13}$$

where $w_t n_t$ is the remuneration of labor, $q_t^k \upsilon_t \bar{k}_{t-1}$ is the remuneration from renting $\upsilon_t \bar{k}_{t-1}$ units of capital services at the rate q_t^k, the term $\vartheta(\upsilon_t) \bar{k}_{t-1}$ describes the cost of capital utilization,[2] f_t are real profits reverted from the firm sector to households in lump-sum transfers, 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 installed capital stock $\overline{k}_t$ according to:

$$\bar{k}_t = (1 - \delta_k) \bar{k}_{t-1} + \varpi_t \left[1 - S\left(\frac{i_t}{i_{t-1}} \right) \right] i_t, \tag{14}$$

where the depreciation rate satisfies $0 < \delta_k < 1$ and $S(\cdot)$ is an adjustment cost function that satisfies: $S(z) = 1$, $S'(z) = 1$ and $S''(\cdot) > 0$. The investment specific shock, ϖ_t, follows the autoregressive process:

$$\ln \varpi_t = \rho_i \ln \varpi_{t-1} + \sigma_i \varepsilon_{i,t} + \sigma_{t+4,i} \psi_{i,t/t+4} + \sigma_{t+8,i} \psi_{i,t/t+8}, \tag{15}$$

with $0 < \rho_i < 1$ and where the zero-mean, serially uncorrelated innovations $\varepsilon_{i,t}$, $\psi_{i,t/t+4}$ and $\psi_{i,t/t+8}$ are normally distributed with standard deviation σ_i, $\sigma_{t+4,i}$ and $\sigma_{t+8,i}$.

[2]The function $\vartheta(\upsilon_t)$ satisfies the conditions: $\vartheta(1) = 0$, $\vartheta'(\cdot) > 0$ and $\vartheta''(\cdot) > 0$.

Thus the household chooses $\left\{c_t, \upsilon_t, i_t, \bar{k}_t\right\}_{t=0}^{\infty}$ to maximize its utility (11) subject to the budget constraint (13) and the evolution of capital stock (14) for all $t = 0, 1, 2, ...$ Letting λ_t and ς_t denote the non-negative Lagrange multipliers with respect to the household's budget constraint and physical capital accumulation equation, the first-order conditions are:

$$\lambda_t \gamma_t = d_t \left(\frac{c_t}{\gamma_t} - h \frac{c_{t-1}}{\gamma_{t-1}} \right)^{-\sigma} - h\beta d_{t+1} \left(\frac{c_{t+1}}{\gamma_{t+1}} - h \frac{c_t}{\gamma_t} \right)^{-\sigma}, \tag{16}$$

$$q_t^k = \vartheta' \left(\upsilon_t \right), \tag{17}$$

$$1 = \Phi_t \varpi_t \left(1 - S\left(\frac{i_t}{i_{t-1}} \right) - S'\left(\frac{i_t}{i_{t-1}} \right) \frac{i_t}{i_{t-1}} \right) + \beta E_t \Phi_{t+1} \mu_{t+1} \frac{\lambda_{t+1}}{\lambda_t} S'\left(\frac{i_{t+1}}{i_t} \right) \left(\frac{i_{t+1}}{i_t} \right)^2, \tag{18}$$

and

$$\Phi_t = \beta E_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \left[\left(1 - \delta_k \right) \Phi_{t+1} + q_{t+1}^k \upsilon_{t+1} - \vartheta \left(\upsilon_{t+1} \right) \right] \right\}, \tag{19}$$

where $\Phi_t = \varsigma_t / \lambda_t$ is the Tobin's Q. According to equation (16), the Lagrange multiplier equals the household's marginal utility of consumption, which accounts for past consumption due to habits in consumption. Equation (17) equates the remuneration of capital with the marginal cost of capital utilization. Finally, equations (18) and (19) describe the evolution of investment and Tobin's Q, respectively.

2.3 The labor 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

$$\mathcal{S}_t^h = w_t - \overline{w}_t + (1 - \delta_{n,t}) \beta E_t \frac{\lambda_{t+1}}{\lambda_t} \mathcal{S}_{t+1}^h, \tag{20}$$

where $\overline{w}_t = (\chi n_t^{\phi})/\lambda_t$ (i.e. the worker's opportunity cost of holding a job comprises the labor 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 (9) with respect to ξ_t, the firm surplus, $\mathcal{S}_t^f$, is given by the marginal product of labor minus the wage and plus the expected surplus in the next period $t+1$ if the match survives separation, which yields

$$\mathcal{S}_t^f = (1-\theta)y_t/n_t - w_t + (1-\delta_{n,t})\beta E_t \frac{\lambda_{t+1}}{\lambda_t}\mathcal{S}_{t+1}^f. \tag{21}$$

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:

$$\mathcal{S}_t^h = \eta(\mathcal{S}_t^h + \mathcal{S}_t^f). \tag{22}$$

Combining equations (20)-(22) and using the first-order condition for vacancies, equation (10), to derive $\mathcal{S}_{t+1}^f = g_{t+1}/q(x_{t+1})$, we can write the agreed wage as:

$$w_t = \eta\left[(1-\theta)y_t/n_t + \beta E_t\left(\lambda_{t+1}/\lambda_t\right) g_{t+1}\right] + (1-\eta)(\chi n_t^{\phi})/\lambda_t. \tag{23}$$

Equation (23) shows that the wage comprises two components. First, for a fraction η, the marginal product of labor 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.

2.4 Model solution

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

$$m_t = \overline{\mu}_t u_t^{\mu} v_t^{1-\mu}, \tag{24}$$

where μ is the elasticity of the matching function with respect to unemployment and $\overline{\mu}_t$ is a shock to the efficiency of matching that follows the autoregressive process

$$\ln \overline{\mu}_t = \left(1-\rho_\mu\right) \ln \overline{\mu} + \rho_\mu \ln \mu_{t-1} + \sigma_\mu \varepsilon_{\mu,t} + \sigma_{t+4,\mu} \psi_{\mu,t/t+4} + \sigma_{t+8,\mu} \psi_{\mu,t/t+8}, \tag{25}$$

with $0 < \rho_\mu < 1$ and where the zero-mean, serially uncorrelated innovations $\varepsilon_{\mu,t}$, $\psi_{\mu,t/t+4}$ and $\psi_{\mu,t/t+8}$ are normally distributed with standard deviation σ_μ, $\sigma_{t+4,\mu}$ and $\sigma_{t+8,\mu}$. Combining the firm's profit conditions (7), the household's budget constraint (13) and the assumption that the government balances the budget with lump-sum transfers produces the aggregate resource constraint

$$y_t = c_t + i_t + v_t g_t + \vartheta\left(\upsilon_t\right) \bar{k}_{t-1}. \tag{26}$$

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 exogenous shocks.[3] The solution to this system is derived using Klein (2000).

3 Econometric methodology, data and prior distribution

We estimate the model using Bayesian methods. To describe the estimation procedure, define Θ as the parameter space of the DSGE model and $Z^T = \{\mathsf{z}_t\}_{t=1}^T$ as the data observed. According to Bayes' Theorem, the posterior distribution of the parameter is of the form $P(\Theta|Z^T) \propto P(Z^T|\Theta)P(\Theta)$. This method updates the *a priori* distribution using the likelihood contained in the data to obtain the conditional posterior distribution of the structural parameters. To approximate the posterior distribution, we employ the random walk Metropolis-Hastings algorithm. The sequence of retained draws is stable, providing evidence on convergence.[4] The posterior density $P(\Theta|Z^T)$ is used to draw statistical inference on the

[3] An appendix that details the steady-state and linearized model is available on request from the authors.

[4] For each chain, we collect 1000000 draws where the first 900000 are discarded and from the remaining 100000 we save one every 100 draws. We have access to a Matlab cluster with 32 workers and we, therefore,

parameter space Θ. An and Schorfheide (2007) and Ruge-Murcia (2007) provide a detailed description of Bayesian simulation techniques applied to the DSGE models.

The econometric estimation uses US quarterly data for the period 1960:1-2007:4. We use data for output growth, consumption growth, investment growth, the unemployment rate and the job-finding rate. The macroeconomic series are an updated version of Smets and Wouters (2007),[5] the unemployment rate is from FRED and the job-finding rate is from Shimer (2012).

Our empirical strategy consists in estimating the 34 parameters in the model that are related to the preferences, technologies and exogenous unanticipated and news disturbances $\{\phi,\ \eta,\ \phi_k,\ h,\ \mu,\ \theta,\ \vartheta,\ q,\ n,\ vg/y,\ \rho_z,\ \rho_a,\ \rho_i,\ \rho_d,\ \rho_{\overline{\mu}},\ \rho_{\delta_n},\ \sigma_z,\ \sigma_a,\ \sigma_i,\ \sigma_d,\ \sigma_{\overline{\mu}},\ \sigma_{\delta_n},\ \sigma_{t+4,z},\ \sigma_{t+4,a},\ \sigma_{t+4,i},\ \sigma_{t+4,d},\ \sigma_{t+4,\overline{\mu}},\ \sigma_{t+4,\delta_n},\ \sigma_{t+8,z},\ \sigma_{t+8,a},\ \sigma_{t+8,i},\ \sigma_{t+8,d},\ \sigma_{t+8,\overline{\mu}},\ \sigma_{t+8,\delta_n}\}$. We calibrate the remaining 9 parameters $\{\beta,\ \delta_n,\ \delta_k,\ \sigma,\ \chi,\ B,\ \alpha,\ a,\ d,\ z,\ \overline{\mu}\}$ whose values fulfill specific economic conditions or determine the steady state of the model. We first describe the calibrated parameters. The quarterly discount factor β is estimated equal to 0.99, which pins down a real interest rate equal to approximately 4 percent, a value commonly used in the literature. Consistent with US data, as in Gertler, Sala and Trigari (2008) and Mumtaz and Zanetti (2012), the value of the exogenous job separation rate, δ_n, is set equal to 10.5 percent, and the value of the capital destruction rate, δ_k, is set equal to 2.5 percent, as in Smets and Wouters (2007). The intertemporal rate of substitution, σ, is set equal to 1 to nest log-utility. We allow the parameter of the disutility of labor, χ, to take the value that enables the model to match the estimated steady-state level of employment equal to 0.70, the average employment rate during the post-war period. Similarly, we allow the scale parameter B to take the value that enables the model to match the estimated share of hiring costs over total output, vg/y, equal to 2 percent.[6] To satisfy the Hosios condition, which ensures that the equilibrium of the decentralized economy is Pareto efficient, we impose that the elasticity of labor market tightness with respect to hiring costs, α, is equal to the relative bargaining power of the worker, $\eta/(1-\eta)$, that is $\eta/(1-\eta) = \alpha$.[7] Finally, we assume that the steady

run 32 chains. An appendix that details evidence on convergence is available on request from the authors.

[5]The data is downloadable from https://www.aeaweb.org/articles.php?doi=10.1257/aer.97.3.586.

[6]By treating χ and B as residuals, we are able to derive closed-form solutions for the steady state of the model.

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

state values of the shocks $\{a,d,z,\overline{\mu}\}$ are conveniently normalized to one.

Tables 2 reports the prior distributional forms, means and standard deviations for the estimated parameters. The priors on these parameters are in line with existent studies and harmonized across different shocks. Naturally, each constrained model uses a subset of these priors. We choose priors for these parameters based on several considerations. The inverse of the Frisch intertemporal elasticity of substitution in labor supply, ϕ, is normally distributed with a prior mean equal to 2, which is in line with micro- and macro-evidence, as detailed in Card (1994) and King and Rebelo (1999), with a standard error equal to 0.25. The wage bargaining parameter, η, is assumed to be beta distributed with prior mean equal to 0.5, as standard in the search and matching literature and with a standard error equal to 0.1. The prior for the parameter controlling the investment adjustment costs, ϕ_k, is normally distributed with a prior mean equal to 5 and a standard error of 0.25. The habit parameter, h, is assumed to be beta distributed with a prior mean equal to 0.75 and a standard error equal to 0.05, as in Smets and Wouters (2007). The elasticity of the matching function, μ, is normally distributed with a prior mean equal to 0.5, as in Petrongolo and Pissarides (2001), and a standard error equal to 0.06. The production capital share, θ, is normally distributed with a prior mean equal to 0.3, a value commonly used in the literature and a standard error of 0.1. The steady-state share of hiring costs over total output, vg/y, is assumed to be normally distributed with a prior mean equal to 0.02, consistent with Gali (2010), and a standard error equal to 0.2. The steady-state vacancy filling probability, q, is assumed to be beta distributed with a prior mean of 0.9, as in Andolfatto (1996), and a standard error equal to 0.05. The steady-state employment rate, n, is assumed to be beta distributed with a prior mean of 0.7 as in the data and a standard error equal to 0.05.

Let's now turn to the prior distributions of the shock parameters. The priors on the autoregressive components and standard errors of the stochastic processes are harmonized across different shocks. We assume that the persistence parameters ρ_z, ρ_a, ρ_i, ρ_d, $\rho_{\overline{\mu}}$ and ρ_{δ_n} are beta distributed, with a prior mean equal to 0.75 and a prior standard deviation equal to 0.1. The standard errors of the unanticipated innovations σ_z, σ_a, σ_i, σ_d, $\sigma_{\overline{\mu}}$ and σ_{δ_n} follow an inverse-gamma distribution with a prior mean of 0.5 and a prior standard deviation of 0.2,

which is similar to Gertler et al. (2008). The standard errors of the anticipated innovations four and eight quarter ahead $\sigma_{t+4,z}$, $\sigma_{t+4,a}$, $\sigma_{t+4,i}$, $\sigma_{t+4,d}$, $\sigma_{t+4,\overline{\mu}}$, σ_{t+4,δ_n}, $\sigma_{t+8,z}$, $\sigma_{t+8,a}$, $\sigma_{t+8,i}$, $\sigma_{t+8,d}$, $\sigma_{t+8,\overline{\mu}}$ and σ_{t+8,δ_n} follow an inverse-gamma distribution with a prior mean of 0.35 and a prior standard deviation of 0.2. To assign equivalent explanation power to unanticipated and news shocks, we have chosen the prior mean distributions of the shocks such that the total variance of the unanticipated component is half of the total variance of the shock.

4 Results

In this section, we present the findings and analyze the model's prediction. To establish the relevance of distinct news shocks, we estimate several versions of the model and assess their empirical fit using the marginal likelihood of the estimated model. Next, we evaluate models' forecasting performance, using both the mean square forecasting error (univariate) and the log-predictive density score (multivariate) metrics. Finally, we investigate the dynamics properties of the model by using impulse response functions, forecasting variance decompositions and historical variance decomposition.

4.1 Model Estimation Fit and Forecasting Performance

The model allows, but does not require, distinct news shocks to interact with unanticipated shocks to generate aggregate fluctuation. To evaluate the importance of the different news shocks we estimate four different versions of the model that embed alternative combinations of news shocks:

- A version of the model without news shocks
- A version of the model with labor market news shocks only (i.e. anticipated shocks to the job destruction rate and matching function)
- A version of the model with macroeconomic news shocks only (i.e. anticipated shocks to stationary TFP, non-stationary labor augmented, consumption preference and investment specific)

- A version of the model with both macro and labor market news shocks

Before looking into the parameters' estimates, we assess the overall performance of competing versions of the model. To establish which theoretical framework better replicates the data, we use the log-marginal likelihood. The log-marginal likelihood represents the posterior distribution, with the uncertainty associated with parameters integrated out, and therefore it also outlines the empirical performance of the model. The log-marginal likelihood is approximated using the modified harmonic mean, as detailed in Geweke (1999). As shown in the fourth row of Table 1, the log-marginal likelihood associated with the model that allows only for macroeconomic news is the highest among the constrained alternatives and equal to -713.06, followed by the model that includes all sources of news shocks that has a log-marginal likelihood equal -797.06. Instead, the versions of the model without any source of news shocks or with labor market news only deliver a worse fit of the data.

Table 1: Log-marginal Likelihood, Model Comparison

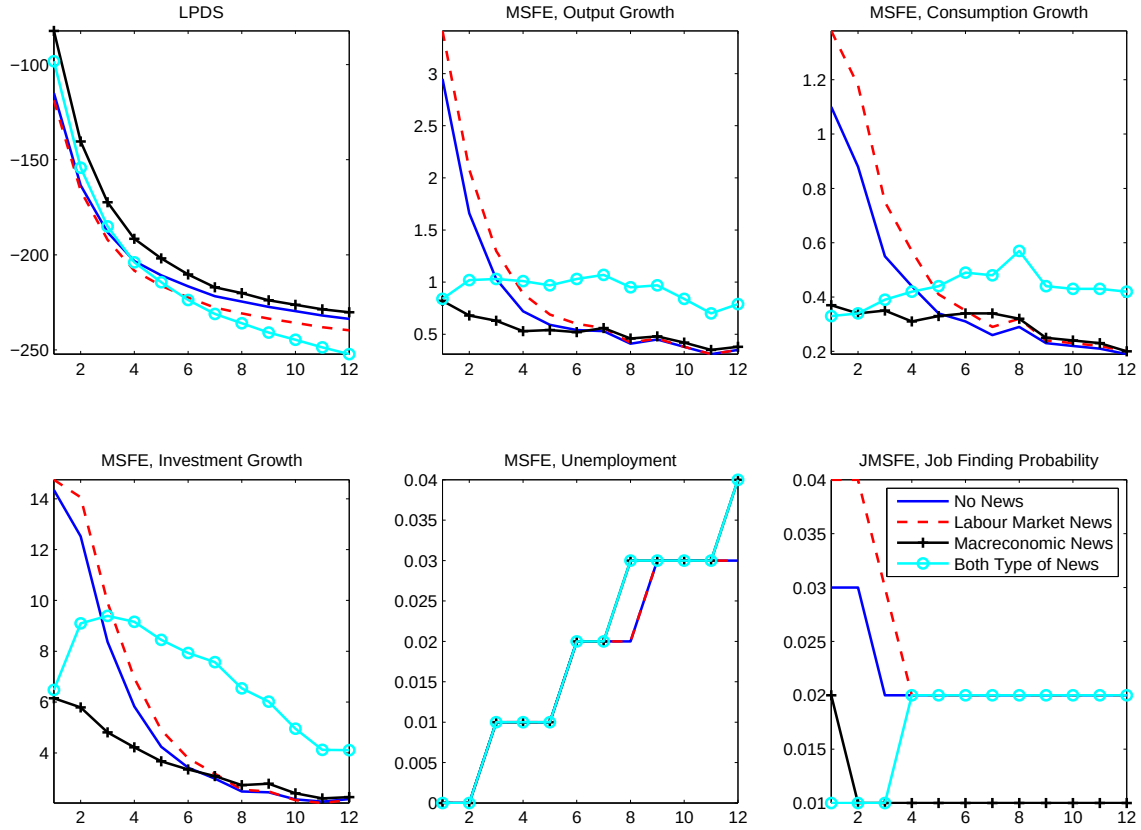
Model	Value
(1) No News	-879.93
(2) Labour Market News	-930.58
(3) Macroeconomic News	-713.06
(4) Macroeconomic and Labour Market News	-797.10

To investigate why the model with macroeconomic news outperforms the alternative models, we use the log-predictive density score (LPDS) and the mean square forecast error (MSFE) for each of the observed variables.[8] We use these metrics based on documentation by Adolfson et al. (2007) of close connection between the log-marginal likelihood and the LPDS of the h-step-ahead predictive density. Futhermore under the normality assumption on the functional form of the predictive density, there is a direct mapping between LPDS and MSFE that makes the MSFE informative on the contribution of each series to generate the results in Table 1. The top-left entry in Figure 1 shows the LPDS, and the remaining entries plot the MSFE of each of the observed variables. The analysis clearly shows that the model with macroeconomic news decreases the MSFE of output growth, consumption growth and

[8]To calculate the LPDS, we follow Adolfson, Linde and Villani (2007) and Warne, Coenen and Christoffel (2013) and assume the predictive density is multivariate normal.

(especially) investment growth. In addition, all models produce an accurate forecast of the unemployment rate and the job-finding probability, although for this last series the model with macroeconomic news outperforms alternative formulations. Hence, the overall superior performance of the model with macroeconomic news is primarily due to its superior forecast of macroeconomic aggregates rather than labor market variables.

Figure 1: Model Forecast Fit

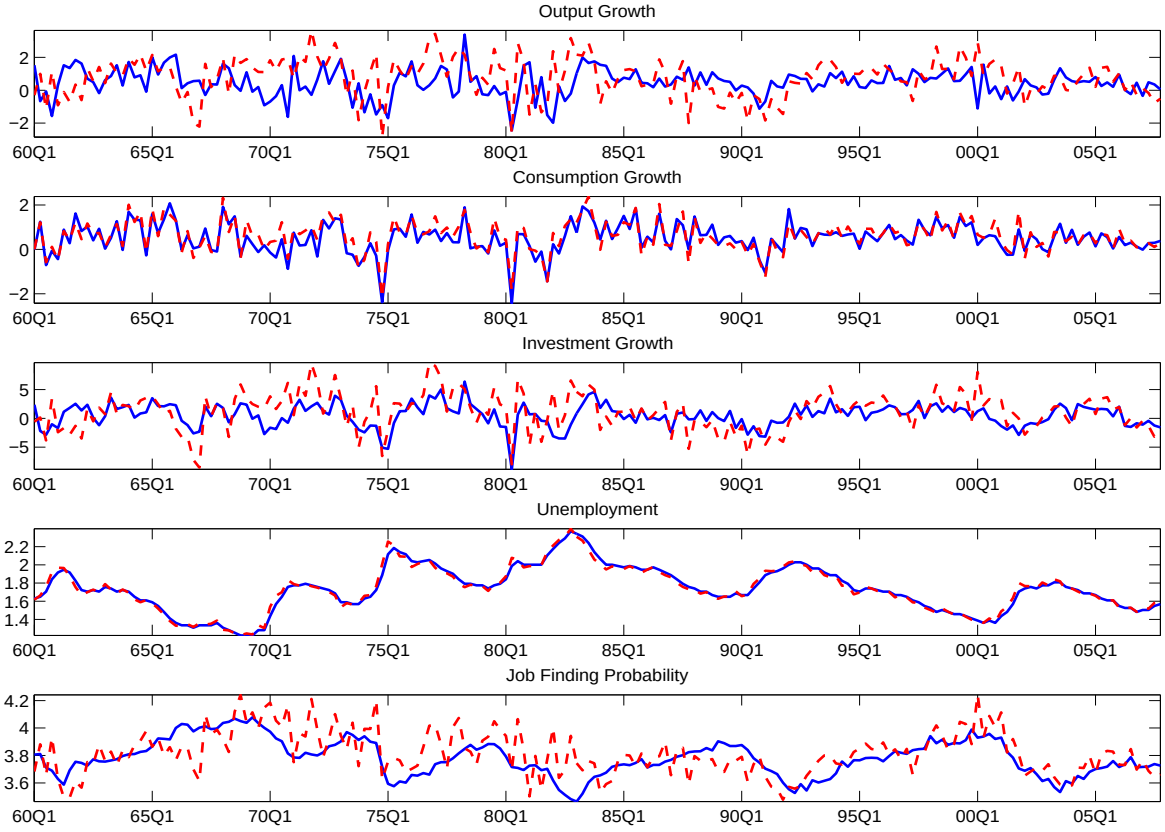


Notes: The top-left entry reports the log-predictive density scores (LPDS) of the h-step ahead predictive density. The remaining entries illustrate the mean square forecast error (MSFE) for each of the variables. The horizontal axes are in quarters.

Interestingly, Figure 1 shows that the MSFE decreases as the forecast horizon increases for all observed series except the unemployment rate. This feature may explains why the multivariate forecasting performance of the model, as represented by the LPDS, deteriorates at higher forecasting horizons. However, unemployment forecast errors are small, suggesting that model's overall forecasting performance increases as the horizon increases. Finally, and importantly, the results on the LPDS in the top-left entry in Figure 1 suggest that the model with macroeconomic news shocks outperforms the alternative versions of the model in the short run (consistent with the results in Table 1 and in line with the results in Adolfson et al. (2007)) as well as in the long run. The rest of the analysis focuses on the model with macroeconomic news that produces the best fit of the data, unless otherwise stated.

To further assess the model's ability to match the data in our sample, Figure 2 compares each observed series (blue solid line) with the corresponding one-period-ahead forecast obtained by applying the Kalman filter on the state-space representation of the model (red dashed line). The latter can be interpreted as the in-sample fit of the model, as discussed by Adolfson et al. (2007) and Del Negro, Schorfheide, Smets and Wouters (2007). Entries shows that the model is able to replicate the unemployment rate and consumption growth closely, and it also performs well in replicating fluctuations in output growth, investment growth and job-finding probability. Overall, considering the simple structure of the model, the fit is quite good.

Figure 2: Model in Sample Fit



Notes: The blue line shows the actual data wile the red-dashed shows the prediction of the Kalman Filter one-step-ahead projection ($E_t x_{t+1}$).

4.2 Parameter Estimates

The last two columns in Table 2 display the value of the posterior mean and standard errors of the structural and shock parameters, respectively. The posterior mean estimates of the structural parameters are remarkably close to those in the literature, indicating that the presence of news shocks does not affect the structural estimates.

The posterior mean of the inverse of the Frisch intertemporal elasticity of substitution in labor supply, ϕ, equals 1.99, which implies a labor supply elasticity approximately equal to 0.5. This value is consistent with those suggested by Rogerson and Wallenius (2009) and more generally with the calibrated values used in the macro literature, as advocated by King and Rebelo (1999). The posterior mean of the wage bargaining parameter, η, is equal to 0.97, which is close to the estimate in Gertler and Trigari (2009). The posterior mean of the investment adjustment cost parameter, ϕ_k, is equal to 6.01, consistent with the estimate in Smets and Wouters (2007). Similarly, the estimate of the habit parameter, h, is equal to 0.95, as in Schmitt-Grohe and Uribe (2012). The estimate of the elasticity of the matching function with respect to unemployment, μ, is equal to 0.75, consistent with Gertler et al. (2008). The estimate of the capital share in production, θ, is equal to 0.28, similar to the standard estimates in the literature. The estimate of the elasticity of the capital utilization rate, ϑ, is equal to 0.28, similar to Gertler et al. (2008). The estimate of the cost of posting a vacancy as a proportion of GDP, vg/y, is equal to 3.27%, slightly higher than values in the literature. Finally, the estimates of the steady-state values of the vacancy filling probability, q, and employment, n, are equal to 0.92 and 0.65 respectively, close to the corresponding values in the data.

The estimates of the autocorrelation coefficients of the unanticipated shocks show that technology shocks (i.e. non-stationary and stationary TFP shocks), investment-specific and preference shocks are highly persistent, with the posterior mean of ρ_z, ρ_a, ρ_i and ρ_d equal to 0.91, 0.95, 0.95 and 0.93, respectively. On the other hand, shocks to the matching function, $\rho_{\overline{\mu}}$, and the job destruction rate, ρ_{δ_n}, are less persistent, with the posterior mean equal to 0.72 and 0.83, respectively. The estimates of the volatility of the unanticipated exogenous

disturbances show that non-stationary TFP shocks are more volatile, with σ_z equal to 0.88, while shocks to stationary TFP, investment-specific technology, consumption preference, the matching function and the job destruction rate are of lower magnitude, with σ_a, σ_i, σ_d, $\sigma_{\overline{\mu}}$ and σ_{δ_n} equal to 0.47, 0.48, 0.48, 0.22 and 0.20, respectively. Clearly, these values suggest that differences among shocks are not sizable.

The estimates of the volatility of the news shocks show that news to investment-specific technology four and eight quarters ahead and to consumption preferences four quarters ahead are highly volatile, with $\sigma_{t+4,i}$, $\sigma_{t+8,i}$ and $\sigma_{t+4,d}$ equal to 4. This finding is consistent with Justiniano, Primiceri and Tambalotti (2010) and Khan and Tsoukalas (2012), who also find similar results in the context of a New Keynesian model. As explained in Justiniano, Primiceri and Tambalotti (2011), investment specific shocks are a proxy of financial frictions, and therefore, sizeable estimates are required to explain sharp movements in investment in the data. Instead, the volatility of other news shocks are of lower magnitude, with $\sigma_{t+4,z}$, $\sigma_{t+8,z}$, $\sigma_{t+4,a}$, $\sigma_{t+8,a}$ and $\sigma_{t+8,d}$ equal to 0.28, 0.45, 0.72, 0.25 and 0.24, respectively.

Table 2: Summary Statistics for the Prior and Posterior Distribution of Parameters

		Prior			Posterior	
Description	Mnemonic	PDF	Mean	Std	Mode	Std
Structural Parameters						
Frisch elasticity	ϕ	Normal	2.00	0.25	1.99	0.25
Bargain power parameter	η	Beta	0.50	0.10	0.95	0.01
Investment adjustment cost	ϕ_k	Normal	5.00	0.25	6.01	0.06
Habit parameter	h	Beta	0.75	0.05	0.93	0.01
Matching function elasticity	μ	Normal	0.50	0.06	0.75	0.01
Production function capital share	θ	Normal	0.30	0.05	0.28	0.01
Utilisation rate elasticity	ϑ	Beta	0.50	0.10	0.28	0.02
Cost of vacancy to GDP steady-state ratio	$\frac{vg}{y}$	Normal	2.00	0.20	3.27	0.02
Steady-state vacancy filling probability	q	Beta	0.90	0.05	0.92	0.04
Steady-state employment	n	Beta	0.70	0.05	0.65	0.03
Shock Persistence Parameters						
Non stationary TFP	ρ_z	Beta	0.75	0.10	0.91	0.01
Stationary TFP	ρ_a	Beta	0.75	0.10	0.95	0.02
Investment specific	ρ_i	Beta	0.75	0.10	0.95	0.01
Consumption preference	ρ_d	Beta	0.75	0.10	0.93	0.01
Matching function productivity	$\rho_{\bar{\mu}}$	Beta	0.75	0.10	0.72	0.02
Job destruction	ρ_{δ_n}	Beta	0.75	0.10	0.83	0.04
Unanticipated Shock Standard Deviation Parameters						
Non stationary TFP	σ_z	Inv-Gamma	0.50	0.20	0.88	0.03
Stationary TFP	σ_a	Inv-Gamma	0.50	0.20	0.47	0.02
Investment specific	σ_i	Inv-Gamma	0.50	0.10	0.48	0.10
Consumption preference	σ_d	Inv-Gamma	0.50	0.10	0.48	0.10
Matching function productivity	$\sigma_{\bar{\mu}}$	Inv-Gamma	0.50	0.20	0.22	0.01
Job destruction	σ_{δ_n}	Inv-Gamma	0.50	0.20	0.20	0.02
News Shock Standard Deviation Parameters						
Non stationary TFP news one year ahead	$\sigma_{t+4,z}$	Inv-Gamma	0.35	0.20	0.28	0.03
Non stationary TFP news two years ahead	$\sigma_{t+8,z}$	Inv-Gamma	0.35	0.20	0.45	0.03
Stationary TFP news one year ahead	$\sigma_{t+4,a}$	Inv-Gamma	0.35	0.20	0.72	0.02
Stationary TFP news two years ahead	$\sigma_{t+8,a}$	Inv-Gamma	0.35	0.20	0.25	0.04
Investment specific news one year ahead	$\sigma_{t+4,i}$	Inv-Gamma	0.35	0.20	4.00	0.06
Investment specific news two years ahead	$\sigma_{t+8,i}$	Inv-Gamma	0.35	0.20	4.00	0.07
Consumption preference news one year ahead	$\sigma_{t+4,d}$	Inv-Gamma	0.35	0.20	4.00	0.06
Consumption preference news two years ahead	$\sigma_{t+8,d}$	Inv-Gamma	0.35	0.20	0.24	0.10

4.3 Impulse Response Analysis

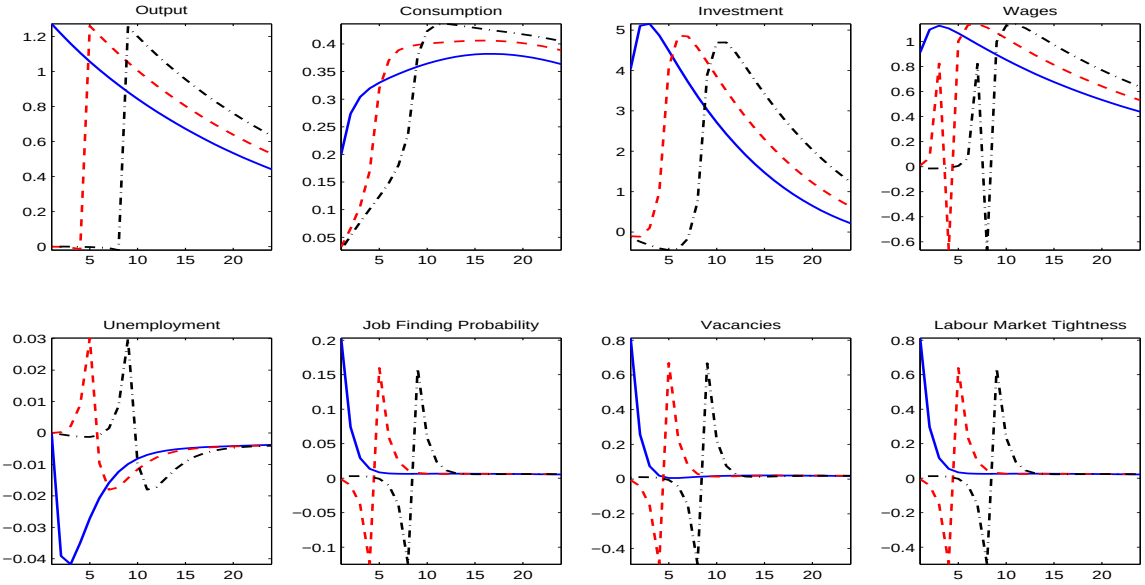
To investigate how key variables of the model react to exogenous unanticipated and news disturbances, Figures 3 and 4 plot impulse response functions of selected variables to a one percent increase in the technology process.[9] The solid line reports the mean responses of an unanticipated shock, while the dashed and dotted-dashed line represents the news shocks four and eight periods a head, respectively. Figure 3 shows the responses of selected variables to a one percent increase in the TFP process. In the aftermath of the unanticipated shock to the stationary TFP, the firm posts more vacancies in the anticipation that the surplus from establishing a match increases and unemployment decreases. High vacancy posting and low unemployment raise labor market tightness, thereby increasing the job-finding rate. The increase in output in response to improved technology generates higher investment and consumption. In general, the variables' reactions to the unanticipated shock to stationary TFP is in line with several studies on RBC models with labor market search frictions.[10]

We can now turn to the variables' responses to the news (i.e. anticipated) shock to the stationary TFP. The variables' responses to the news shock four and eight quarters ahead are represented by the dashed and dotted-dashed line, respectively. Since the responses are similar across different horizons, we focus the analysis on the four-quarter ahead, but similar considerations hold for eight-quarter ahead. In the anticipation of an increase in the stationary TFP shock, consumption raises and capital utilization decreases since improved productivity in the future reduces the need of using input of production. Movements in consumption and investment offset each others, resulting in a stable output. Unchanged output and decreased capital utilization induce the firm to decrease labor input, thereby raising the marginal product of labor and the wage. The increase in the wage leads the firm to reduce the number of vacancies and therefore labor market tightness and the job-finding probability fall. Once the TFP shock realizes in the fourth quarter, employment sharply increases, reducing the marginal product of labor and consequently wages. The fall in wages

[9] An appendix that details impulse responses to the other shocks in the model is available on request from the authors.

[10] See, among others, Shimer (2005) and Mandelman and Zanetti (2014).

Figure 3: Responses to 1% Increase to Stationary TFP Process

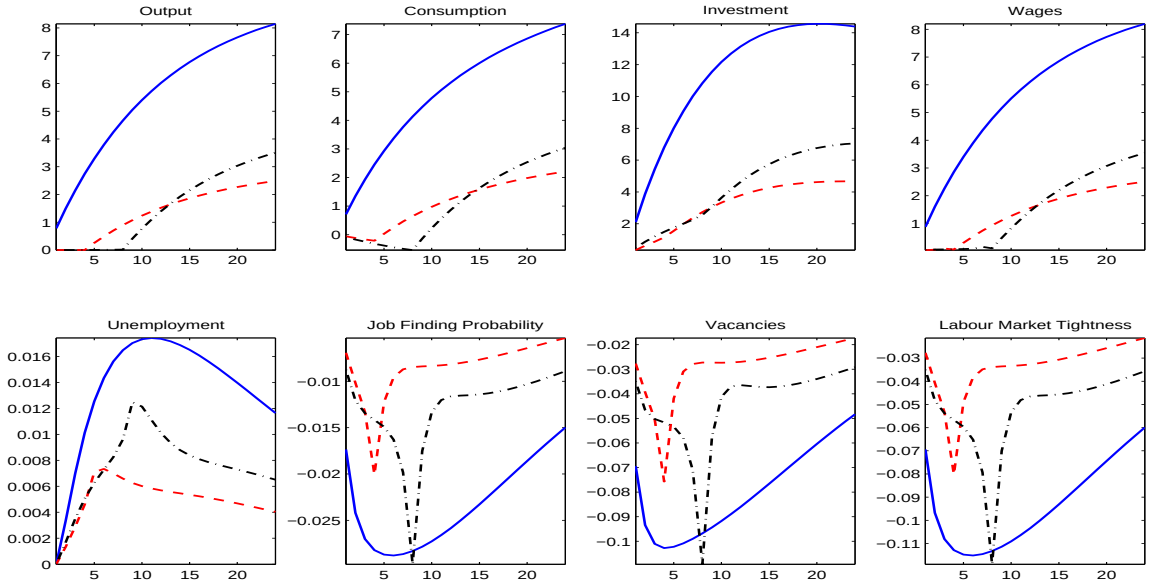


Notes: Each entry shows the percentage-point response of one of the model's variables to a one percentage increase in the shock. The solid line reports the unanticipated shock, the dashed line reports the four-quarter ahead anticipated shock and the dashed-dotted line reports the eight-quarter ahead anticipated shock.

increases vacancy posting, labor market tightness and the job-finding probability. Output rises, unemployment falls and the wage increases. Thereafter the responses of the variables is similar to those of an unanticipated stationary TFP shock, and the variables slowly converge to the equilibrium due to the high value (0.95) of the autoregressive component.

Figure 4 plots the variables' responses to the non-stationary, labor augmented shock. In the aftermath of the unanticipated shock to the non-stationary TFP, the firm increases output, investment and wage. The increase in the wage reduces the overall surplus from establishing a match and induces the firm to decrease vacancy posting, which increases unemployment and leads to a fall in the job-finding probability. Note that the fall in unemployment in response to the non-stationary TFP shock is consistent with the findings in Linde (2009), who shows that TFP shocks persistent in growth term generate an income effect that reduces labor input. Similarly, this finding is consistent with Mandelman and Zanetti (2014), who show that TFP shocks lead to an increase in unemployment if the recruitment costs are sufficiently high. The red dashed line shows the variables' responses to the anticipated news shock four-

Figure 4: Responses to 1% Increase to Non-Stationary TFP Process



Notes: Each entry shows the percentage-point response of one of the model's variables to a one percentage increase in the shock. The solid line reports the unanticipated shock, the dashed line reports the four-quarter ahead anticipated shock and the dashed-dotted line reports the eight-quarter ahead anticipated shock.

quarter ahead. In the anticipation of an increase in the non-stationary TFP shock, output and investment rise. The agents anticipate that permanent higher productivity leads to higher capital utilization that entails high investment adjustment costs, whose effect is to induce an increase in current savings and therefore a fall in consumption in anticipation of the shock. Movements in investment and consumption offset each other, leaving output unchanged. Since in the fourth quarter TFP will increase permanently, vacancy posting falls in the anticipation period, thereby increasing unemployment and consequently reducing labor market tightness and the job-finding probability. Once the shock materializes in the fourth quarter, output increases, leading to a positive surplus from establishing a match. Therefore, the firm raises vacancy postings sharply, reducing unemployment, decreasing labor market tightness and the job-finding probability. Note that the variables responses to the anticipated shock after the realization of the shock (i.e. fourth quarter) are similar to those of the unanticipated shock whereas they differ in the anticipation phase. This result is in general consistent with studies that identify news shocks as an important propagation channel, as outlined in Beaudry and

Portier (2013).

4.4 Forecast Variance Decomposition Analysis

To understand the extent to which each shock explains movements in the variables, Table 3 reports the asymptotic forecast error variance decompositions. The entries show that unanticipated stationary TFP shocks are important at a one-quarter horizon as they explain the bulk of fluctuations in the growth of output and investment, wage, vacancies and labor market tightness. News shocks in TFP, investment-specific and preferences explain slightly less than half of fluctuations in consumption growth. Also, shocks to the job destruction probability and matching function play a minimal role to economic fluctuations. In general, the analysis shows that unanticipated shocks play a more relevant role than news shocks to explain variables' fluctuations at short run horizons. However, news shocks become more important to explain economic fluctuations at longer horizons. For instance, at one year horizon, news to non-stationary TFP shocks explain 22 percent and 12 percent of consumption and investment, respectively. They also explain 6 percent of fluctuations in vacancies and labor market tightness. Stationary TFP shocks explain 34 percent approximately of fluctuations in vacancies and labor market tightness, and 15 percent approximately of movements in wages.

Table 3: Forecast Variance Decomposition

	Non-Stationary TFP		Stationary TFP		Investment Specific		Consumption Preference		Matching Production	Job Destruction
	Shock	News	Shock	News	Shock	News	Shock	News		
1 Quarter horizon										
Output	2.2	0.0	97.6	0.0	0.0	0.0	0.0	0.0	0.1	0.1
Consumption	43.7	20.6	12.4	0.8	0.3	13.3	0.6	8.3	0.0	0.0
Investment	28.0	6.7	60.3	0.1	0.1	2.0	0.2	2.4	0.1	0.1
Wages	0.2	2.8	95.7	0.0	0.1	0.1	0.2	0.7	0.1	0.0
Unemployment	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Job Finding Probability	0.7	0.3	15.0	0.0	0.0	0.0	0.0	0.1	83.9	0.0
Vacancies	4.3	1.7	93.2	0.0	0.1	0.0	0.0	0.5	0.1	0.0
Labor Market Tightness	4.3	1.7	93.2	0.0	0.1	0.0	0.0	0.5	0.1	0.0
4 Quarters horizon										
Output	11.9	0.0	87.5	0.0	0.0	0.0	0.0	0.0	0.2	0.3
Consumption	45.4	21.8	3.9	1.4	0.3	17.3	0.5	9.4	0.0	0.0
Investment	48.0	11.6	29.9	0.8	0.2	6.5	0.2	2.6	0.1	0.1
Wages	0.9	1.0	25.8	14.7	0.0	0.3	0.0	57.1	0.0	0.0
Unemployment	1.1	0.4	4.7	0.2	0.0	0.0	0.0	0.0	47.9	45.7
Job Finding Probability	2.6	1.4	8.5	7.0	0.0	0.1	0.0	0.6	79.8	0.0
Vacancies	11.8	6.1	41.0	33.8	0.2	0.3	0.0	3.3	1.8	1.8
Labor Market Tightness	13.0	6.7	42.1	34.4	0.2	0.3	0.0	3.2	0.1	0.1
12 Quarters horizon										
Output	16.5	0.8	28.5	53.7	0.0	0.4	0.0	0.0	0.1	0.1
Consumption	43.4	20.3	1.3	3.0	0.2	24.5	0.3	7.1	0.0	0.0
Investment	50.4	14.5	6.1	11.6	0.1	13.3	0.2	3.9	0.0	0.0
Wages	6.4	1.1	21.7	46.9	0.0	3.1	0.0	20.7	0.0	0.0
Unemployment	4.5	2.3	2.1	1.9	0.0	2.1	0.0	0.8	35.8	50.4
Job Finding Probability	6.6	3.4	6.2	15.5	0.1	4.7	0.0	1.5	62.1	0.0
Vacancies	14.0	7.3	16.2	43.5	0.1	10.8	0.0	3.4	1.9	2.8
Labor Market Tightness	17.4	8.9	16.3	40.8	0.1	12.4	0.0	3.9	0.1	0.0
40 Quarters horizon										
Output	21.8	5.1	18.5	46.3	0.0	7.4	0.0	0.8	0.0	0.0
Consumption	45.8	22.0	1.0	2.8	0.1	18.6	0.2	9.6	0.0	0.0
Investment	56.6	22.8	1.9	4.4	0.0	9.0	0.1	5.2	0.0	0.0
Wages	12.1	3.2	16.4	45.0	0.1	11.3	0.0	11.8	0.0	0.0
Unemployment	9.8	4.6	1.9	1.9	0.0	5.6	0.0	1.0	30.1	45.0
Job Finding Probability	10.5	5.1	5.7	14.2	0.1	6.7	0.0	1.5	56.1	0.0
Vacancies	19.5	9.6	13.7	36.8	0.1	13.1	0.0	3.1	1.6	2.5
Labor Market Tightness	24.0	11.6	13.0	32.4	0.1	15.4	0.0	3.4	0.0	0.0

At longer horizons, the contribution of news shocks to movements in the variable is more sizeable. For instance, at ten-year horizon, news shocks to stationary TFP explain 54 percent of fluctuations in output and wages, and they explain approximately 47 percent and 45 percent of movements in vacancies and labor market tightness, respectively. News shocks explain the bulk of fluctuations in wages, vacancies and labor market tightness, and they compete with unanticipated shocks to explain fluctuations in the growth rate of output, consumption and investment. Finally, news shocks explain a limited fraction of fluctuations in unemployment and the job-finding probability. To summarize, news shocks have limited influence in short-run movements, but they explain a sizeable portion of long- and medium-run fluctuations, except for unemployment and the job-finding rate. These findings show that news shocks are a relevant source of movements for key labor market variables (i.e. wages, vacancies and labor market tightness). In addition, in line with Schmitt-Grohe and Uribe (2012), Christiano, Motto and Rostagno (2014) and Gortz and Tsoukalas (2011), news shocks explain a sizeable fraction of movements in macroeconomic variables. Finally, it is interesting to note that unanticipated shocks to the job destruction rate explain the bulk of fluctuations in unemployment from the fourth quarter ahead onwards.

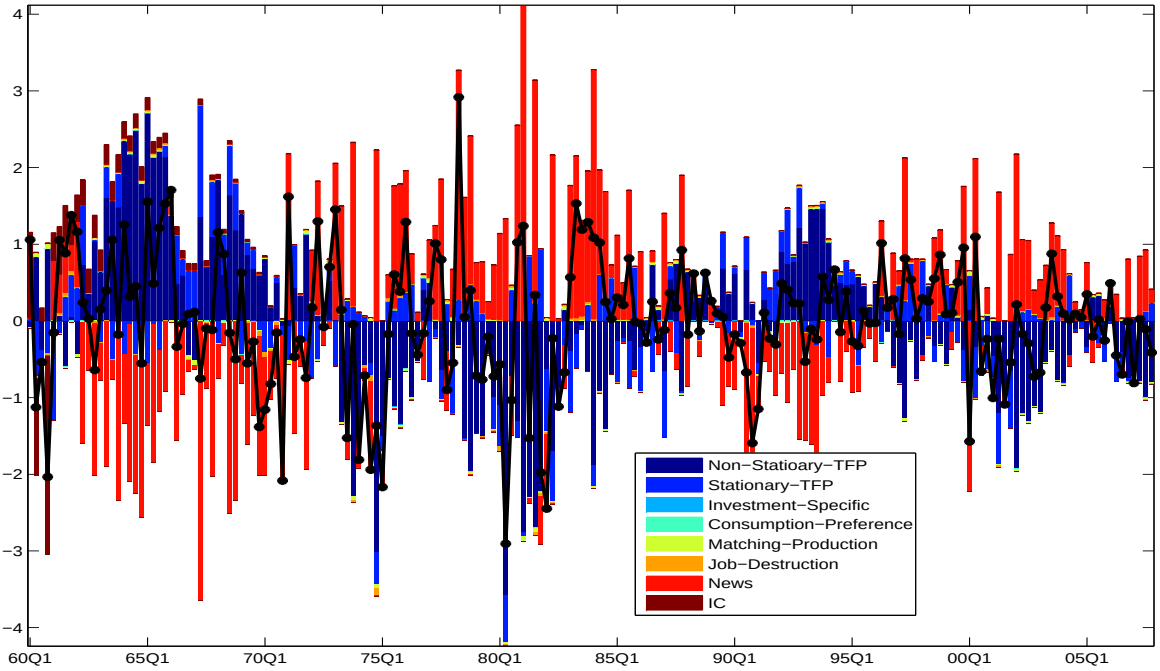
4.5 Historical Decomposition Analysis

It is interesting to use the model to derive the variables' historical decomposition over the sample period. In this way, we can study how news shocks have contributed to historical movements in the data. Figures 5-7 report the historical decompositions that display the contribution of news shocks to movements in the growth rate of output, unemployment and the job-finding probability over the period 1960:1-2007:4.[11] A number of interesting facts stand out. First, the contribution of news shocks to output growth is significant throughout the sample period, with a negative contribution during the mid-1960s until the mid-1970s, followed by a positive contribution until the late 1980s. From the early 2000s until the end of the sample period, the contribution of news shocks is positive. Second, news shocks are

[11] The historical decompositions for the growth rate of consumption and investment are similar to the historical decomposition of output growth. An appendix that details the historical decompositions for these variables is available on request to the authors.

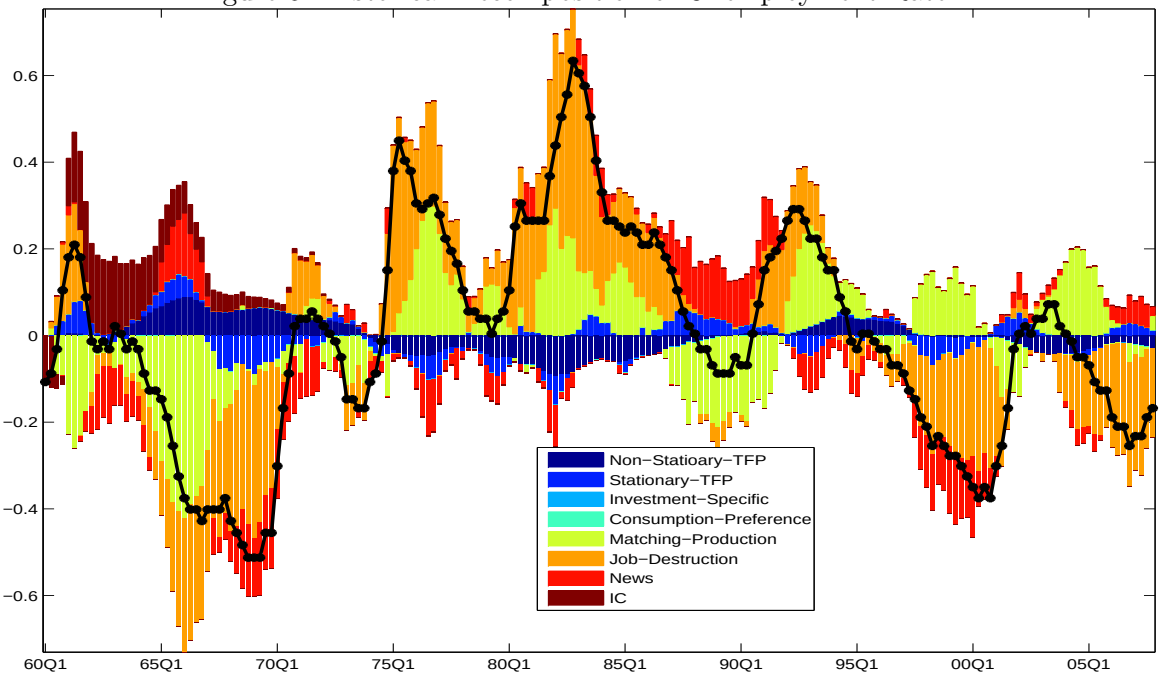
important for fluctuations in the unemployment rate over the periods 1960-1974 and 1988-2007, and their contribution declines over the rest of the sample period. In particular, the contribution of news shocks is the lowest during the period from the late 1960s to the mid-1975s, which coincides with the oil crisis. News shocks also are relevant for the mid-1980 and late-1990 periods. Finally, news shocks play a relevant role for historic movements in the job-finding probability, although their contributions display no recurrent patterns and they alternate positive to negative contributions throughout the sample period. From this exercise, we can draw some interesting observations. News shocks are an important source of fluctuations in the observed variables, especially for the growth rates of output, consumption, investment and the job-finding rate, but they have limited influence on the unemployment rate. Overall, however, the bulk of macroeconomic fluctuations is explained by unanticipated shocks, especially shocks to non-stationary and stationary TFP, in line with the results in Khan and Tsoukalas (2012).

Figure 5: Historical Decomposition of Output Growth



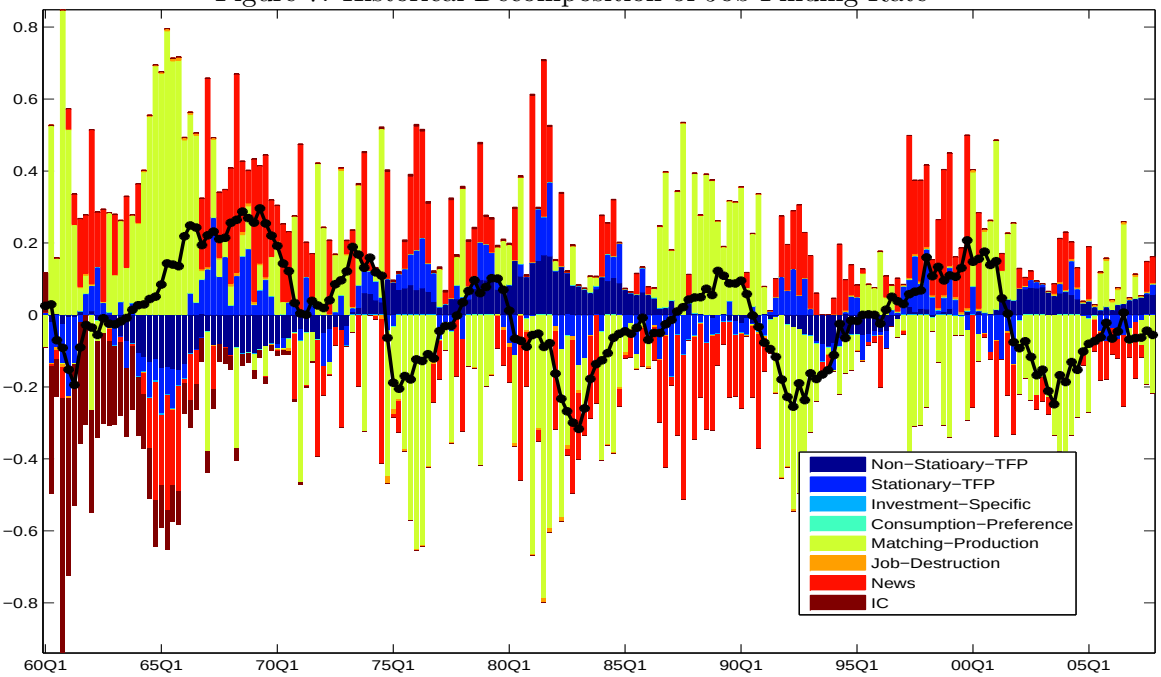
Notes: The figure shows the historical variance decomposition of output growth. The solid line reports output growth in the data.

Figure 6: Historical Decomposition of Unemployment Rate



Notes: The figure shows the historical variance decomposition of the unemployment rate. The solid line reports unemployment rate in the data.

Figure 7: Historical Decomposition of Job Finding Rate



Notes: The figure shows the historical variance decomposition of the job finding rate. The solid line reports the job finding rate in the data.

5 Conclusion

This paper has investigated the effect of news shocks on labor market variables using a baseline general equilibrium model with search and matching frictions on the labor market and real frictions. News shocks are a relevant source of aggregate fluctuations and in movements of labor market variables. In particular, the analysis confronts the model with the data using Bayesian inference and establishes that news shocks to stationary and non-stationary TFP, investment-specific productivity and preference shocks are critical to explain aggregate dynamics, and they produce a remarkable fit of the data. The inclusion of labor market news shocks (i.e. anticipated shocks to the matching technology and the job destruction rate) worsen the model forecast fit of the growth of output, consumption and investment in the data. News shocks are powerful tools to explain movements in the variables in the medium- and long-run (four-quarter ahead and onwards) whereas unanticipated shocks explain the bulk of fluctuations in the short run (one-quarter ahead). The analysis shows that the responses of macroeconomic aggregates in the anticipation phase of the news shock differ from responses in the aftermath of the realization of the shock. In particular, in the aftermath of the shocks, the dynamics of the model are similar to the responses of the unanticipated shock.

This paper puts forward a few valuable extensions for future research. First, the analysis shows that in a model with news shocks, unanticipated shocks to the job destruction rate play a non-trivial role in explaining fluctuations in unemployment. 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, real wage rigidities are a relevant device used to improve the performance of search and matching models of the labor market to replicate important stylized facts in the data, as shown in Gertler and Trigari (2009). It would be interesting to investigate the role of wage rigidities in the context of news shocks.

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