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News Driven Business Cycles and data on asset prices in estimated DSGE models ☆

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ABSTRACT

We demonstrate that inference from estimated structural News Driven Business Cycle (NDBC) models about the main drivers of fluctuations in macroeconomic variables and asset prices is sensitive to assumptions about the structure of the news shock processes. We show that, when data on asset prices are used in the estimation, a long-run news shock specification has a better fit than the short-run news shock specification which is prevalent the existing literature. The variance decompositions from the former model specification reveal that long-run news shocks are not the main drivers of macroeconomic variables, but do account for the majority of aggregate stock market fluctuations.

1. Introduction

There exists a large body of literature that emphasizes the possibility that news shocks, or changes in economic agents' expectations about the future values of fundamentals, play an important role in driving macroeconomic fluctuations. This idea, whose origins can be traced back to Pigou (1926) and Clark (1934), has been recently revived by Beaudry and Portier (2004, 2006), Christiano et al. (2008), and Jaimovich and Rebelo (2009). A major strand in this rapidly-growing literature estimates structural News Driven Business Cycle (NDBC) models (i.e. fully-specified DSGE models that feature both, unanticipated shocks and news shocks) and uses the results in order to quantify the relative contribution of news shocks in driving macroeconomic fluctuations (Davis, 2007; Khan and Tsoukalas, 2010; Fujiwara et al., 2011; Schmitt-Grohe and Uribe, 2012). The essence of any estimation exercise that belongs to this strand of the literature consists in using data on directly observable variables (e.g. macroeconomic aggregates, asset prices, etc.) in combination with model-implied relationships between those variables and the model's unobserved states (e.g. unanticipated shocks and news shocks) in order to extract information about the latter.

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The benchmark estimates of virtually all papers in the existing NDBC literature are obtained using mainly data on macroeconomic variables and largely ignoring data on asset prices.[1] This practice is quite surprising considering the existence of a large empirical literature which suggests that stock price movements reflect changes in economic agents' expectations of future developments in the economy (e.g. Fama, 1990; Schwert, 1990; Beaudry and Portier, 2006, etc.). Given this body of evidence, not including data on asset prices in the estimation of a structural NDBC model would only be justified if all the information about changes in expectations that is contained in asset prices could be extracted by using solely macroeconomic variables. If this was the case, adding data on asset prices in the estimation would be unnecessary as it would not add any new information about the unobserved shock processes and would not alter the results obtained by using only data on macroeconomic variables.

Nevertheless, there is no paper in the existing literature that systematically examines the extent to which including data on asset prices in the estimation of a structural NDBC model has an impact on inference about the main drivers of business cycle fluctuations. The authors of several papers (Davis, 2007; Khan and Tsoukalas, 2010; Schmitt-Grohe and Uribe, 2012) re-estimate their benchmark models after adding stock prices to the set of observable variables as a robustness check. All of them conclude that adding data on stock prices has only a marginal impact on inference about the main sources of business cycle fluctuations and as a result do not include such data in their benchmark estimations. As we show below, such conclusions are sensitive to assumptions about the structure of the news shock processes.

This paper is the first to formally study the impact of including data on asset prices in the estimation of a structural NDBC model while allowing for alternative specifications for the structure of the news shock processes. Our results indicate that, when asset prices are included in the vector of observables, a long-run news shock specification fits the data better than the short-run news shock specification which is prevalent the existing literature. The variance decompositions implied by the former model specification suggest that long-run news shocks are not the main drivers of macroeconomic variables, but do account for the majority of aggregate stock market fluctuations.

The analysis is performed in several steps. We start by solving a structural NDBC model under the two alternative assumptions about the structure of the news shock processes discussed above. Next, we use Bayesian Markov Chain Monte Carlo (MCMC) methods in order to estimate each model specification using data on asset prices in addition to data on macroeconomic variables. After that, we compare the marginal likelihoods of the two alternative model specifications. We then select the model specification with the best fit and use the estimates of the structural parameters and the unobserved states from that specification in order to make an inference about the main drivers of fluctuations in the observable variables.

Our theoretical framework is most closely related to the one used in Schmitt-Grohe and Uribe (2008). We focus on a real business cycle (RBC) model that is augmented with four real rigidities: capital adjustment costs, variable capacity utilization, internal habit formation in consumption, and internal habit formation in leisure. The first three of the above rigidities have been shown to improve the empirical fit of NDBC models and are fairly standard in the existing literature. The last rigidity, internal habit formation in leisure, is introduced because, as discussed in Schmitt-Grohe and Uribe (2008), it has the potential to dampen the wealth effect of anticipated changes in productivity on labor supply.

We recognize that casting the model in a New Keynesian setting rather than in the real business cycle environment that we focus on may improve its ability to fit the macro data. However, the main objective of the paper is not to propose a model that produces the best possible fit for the macro data alone – numerous other papers have already done that. Instead, the paper's main goal is to demonstrate that, when data on asset prices are included in the estimation of a structural NDBC model, the long-run news shock specification has a better fit than the traditional short-run news shock specification. Keeping in mind that two of the seminal papers in the NDBC literature (Beaudry and Portier, 2004; Jaimovich and Rebelo, 2009) are set in a real business cycle framework, we believe that obtaining the above result in such a setting is an important finding on its own. While exploring whether this result also holds in a New Keynesian setting would be an intriguing exercise, it is beyond the scope of this paper.

The model is driven by the four exogenous shock processes which govern the evolution of labor augmenting technology (LAT), investment-specific productivity (ISP), total factor productivity (TFP), and the marginal efficiency of investment (MEI). Each of the exogenous driving processes is subject to two types of shocks – unanticipated shocks and news shocks.

We consider two alternative news shock specifications. In the first one, news shocks are modeled as one-off shocks to fundamentals which materialize n $(n = 1, 2, 3\ldots)$ periods after they enter the information set of the representative agent. We call that the short-run news (SRN) specification. This is the only specification that is considered by the vast majority of the estimated structural NDBC literature (e.g. Davis, 2007, Khan and Tsoukalas, 2010; Fujiwara et al., 2011; Schmitt-Grohe and Uribe, 2012). As Walker and Leeper (2011) point out, it is quite surprising that, despite the centrality of the exact structure of information flows to the NDBC literature, there has been virtually no examination of alternative equally plausible information flow structures.

This prompts us to explore an alternative specification for the structure of the news shock processes. Our choice of an alternative specification is motivated by the combination of two facts. First, asking the model to fit data on asset prices is a crucial part of our experiment. Second, as demonstrated by the asset pricing literature on long-run risks

[1] A small number of papers (Davis 2007; Khan and Tsoukalas, 2010; Fujiwara et al., 2011) have used interest rates, but not stock prices, as observables in their benchmark estimations.

(Bansal and Yaron, 2004; Piazzesi and Schneider, 2007; Hansen et al., 2008; Eraker and Shaliastovich, 2008; Bansal et al., 2010; Drechsler and Yaron, 2011, etc.), introducing long-run predictable components in the exogenous shock processes can help explain key asset pricing phenomena. That is why we consider a specification, originally introduced by Cochrane (1994), in which news shocks manifest themselves in the form of shocks to the long-run components of economic fundamentals, but have no impact on fundamentals in the period in which they enter the information set of the representative agent. We call that the long-run news (LRN) specification. Our paper is the first to incorporate the long-run news shock specification into an estimated structural NDBC model. Furthermore, it is also the first to compare the empirical performance of that specification against the performance of the traditional short-run news shock specification.

In order to account for the fact that linearized DSGE models tend to have a hard time fitting data on asset prices, we follow the approach of Justiniano et al. (2013) and allow for measurement errors in the observation equations for the two asset price variables (i.e. total market valuation and the real risk-free interest rate).[2] These measurement errors could be interpreted as terms that capture the mismatch between the data and the model's asset price concepts. We infer the scale of that mismatch by estimating the size of the measurement errors. When doing that, we follow the approach of Schmitt-Grohe and Uribe (2012) by imposing upper bounds on the prior distributions of the measurement errors, which are functions of the standard deviations of the respective observable variables. This allows us to take advantage of the fact that the model-implied asset price variables could be mapped, albeit imperfectly, onto the asset price variables observed in the data and, as a result, the latter could be used to extract information about the unobserved shock processes in NDBC models that cannot be obtained from macroeconomic data alone.

Our results indicate that, when asset prices are included in the set of observable variables, the long-run specification for the structure of the news shock processes fits the data better than the short-run specification which is prevalent in the existing NDBC literature. The results from the long-run news specification imply that most of the variation in macroeconomic aggregates is attributed to unanticipated total factor productivity shocks and unanticipated shocks to the marginal efficiency of investment. Meanwhile, long-run news shocks do not play a major role, accounting for less than a quarter of the variance of output growth and consumption growth and for roughly a third of the variance of hours. This finding stands in sharp contrast to the results of the rest of the NDBC literature, which assign a considerably larger share of the variance of macroeconomic variables to news shocks. Our results also suggest that long-run news shocks are a major driver of aggregate stock market fluctuations, accounting for 84% of the variance of that series.

In addition to the papers on estimated structural NDBC models listed above, our paper is related to two other branches of the expectation driven cycles literature. The first one, which includes the papers of Beaudry and Portier (2006), Beaudry and Lucke (2010), and Barsky and Sims (2011), uses empirical tools such as structural vector autoregressions and structural vector error-correction models in order to quantify the importance of news shocks in business cycle fluctuations. Our paper is also related to the purely theoretical strand of the expectation driven cycles literature (Beaudry and Portier, 2004, 2007; Christiano et al., 2008; Jaimovich and Rebelo, 2009; Karnizova, 2010), which focuses on examining mechanisms through which the comovement properties of macroeconomic aggregates over the business cycle are preserved in response to a news shock.

Finally, in a broader sense, our paper is also related to the strand of the literature that uses the results obtained from the estimation of fully-specified DSGE models which contain only unanticipated shocks (i.e. models which do not allow for news shocks) in order to make inferences about the main drivers of business cycle fluctuations. The most prominent representatives of that body of literature are Smets and Wouters (2007) and Justiniano et al. (2010, 2011).

The rest of the paper is organized as follows. We describe our theoretical framework in Section 2. In Section 3, we go over the estimation procedure. In Section 4, we compare the results from the two alternative model specifications that we estimate. In Section 5, we examine the main drivers of fluctuations in macroeconomic variables and asset prices. We conclude in Section 6.

2. Theoretical framework

This section presents the theoretical framework that we use in this paper. We start by describing the model economy. Next, we introduce the two alternative specifications for the structure of the exogenous driving processes that we consider. Finally, we go over the methodology that we use to solve each model specification.

2.1. The model economy

The model economy is populated by a large number of identical, infinitely lived agents. The representative agent derives utility from consumption (C_t) and leisure (l_t), and maximizes:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left\{ \frac{[(C_t - \theta_c C_{t-1})(l_t - \theta_l l_{t-1})^{\chi}]^{1-\gamma} - 1}{1-\gamma} \right\}, \tag{1}$$

[2] Justiniano et al. (2013) allow for measurement errors in wages when estimating a DSGE model of the US economy in order to account for the mismatch between the data and the model's wage concept.

where E_0 denotes the expectation conditional on the information available at time zero, $\beta \in (0,1)$ denotes the subjective discount factor, $\gamma > 0$ is the inverse of the intertemporal elasticity of substitution, $\theta_c \in [0,1)$ governs the degree of internal habit in consumption, $\theta_l \in [0,1)$ governs the degree of internal habit in leisure, and $\chi > 0$ is the parameter that controls the Frisch elasticity of labor supply.

Recently, many papers in the NDBC literature have opted to use the utility function introduced by Jaimovich and Rebelo (2009) due to the fact that it helps generate a comovement in macro variables in response to a TFP news shock by minimizing its short-run wealth effect on labor supply. Nevertheless, instead of assuming the preference specification proposed by Jaimovich and Rebelo (2009), we follow Schmitt-Grohe and Uribe (2008) in our choice of utility function due to several reasons. First, focusing on the preference specification in (1) facilitates the comparison of our results with those of Schmitt-Grohe and Uribe (2008). Second, Barsky and Sims (2011) provide empirical evidence that TFP news shocks do not trigger a positive comovement among macro variables and argue that the "excessive focus on the impact effects of news shocks has been somewhat misplaced." Third, the only news shocks that are studied in Jaimovich and Rebelo (2009) are TFP news shocks and ISP news shocks (i.e. their paper does not explore LAT news shocks and MEI news shocks). Fourth, as discussed in Schmitt-Grohe and Uribe (2008), assuming internal habit in leisure also dampens the wealth effect of anticipated changes in productivity on labor supply.

Agents split their time endowment between leisure and hours worked (h_t). We normalize the total time endowment per period to unity:

$$h_t + l_t = 1. \tag{2}$$

Output (Y_t) is produced with a Cobb–Douglas production function using capital services and labor:

$$Y_t = Z_t F(u_t K_t, X_t h_t) = Z_t\big[(u_t K_t)^{\alpha}(X_t h_t)^{1-\alpha}\big], \tag{3}$$

where Z_t represents the level of total factor productivity (TFP), which is assumed to be stationary, and X_t represents the level of labor-augmenting technology (LAT), which is assumed to be non-stationary. Capital services are equal to the product of the existing capital stock (K_t) and the rate of capacity utilization (u_t).

The stock of capital evolves according to the following law of motion:

$$K_{t+1} = (1-\delta)K_t + \Omega_t\big[I_t - \Phi(\cdot)\big], \tag{4}$$

where I_t denotes gross investment, Ω_t is a stationary shock to the marginal efficiency of investment (MEI), and $\Phi(\cdot)$ is the capital adjustment costs function. The MEI shock (Ω_t) represents an exogenous disturbance to the process which transforms investment goods into capital goods. It has been identified by Justiniano et al. (2011) as a major source of business cycle fluctuations.

In this model economy, increasing the rate of capacity utilization is costly because it causes a faster rate of capital depreciation. More specifically, the rate of depreciation, $\delta(\cdot)$, has the following functional form:

$$\delta(u) = \delta_0 + \delta_1(u-1) + \frac{\delta_2}{2}(u-1)^2, \tag{5}$$

where $\delta_0 > 0$, $\delta_1 > 0$, $\delta_2 > 0$.

Capital adjustment costs are a function of the ratio of investment to existing capital ($\frac{I_t}{K_t}$) as in Hayashi (1982), Abel and Blanchard (1983), and Shapiro (1986):

$$\Phi(\cdot) = \Phi_C\left(\frac{I_t}{K_t}\right)K_t = \frac{1}{2\delta_0\eta}\left(\frac{I_t}{K_t} - \tau\right)^2 K_t, \tag{6}$$

where τ is the steady-state investment–capital ratio, $\eta > 0$ is the elasticity of the investment–capital ratio with respect to Tobin's q, and δ_0 is the steady state rate of capital depreciation.[3]

The economy's resource constraint is:

$$Y_t = C_t + I_t A_t, \tag{7}$$

where A_t is the technical rate of transformation between consumption and investment goods. We assume that it is exogenous, stochastic, and non-stationary. In the rest of the paper, we refer to it as an investment specific productivity (ISP)

[3] We also consider a specification for $\Phi(\cdot)$ in which adjustment costs are a function of the growth rate of investment ($\frac{I_t}{I_{t-1}}$) as in Christiano et al. (2005):

$$\Phi(\cdot) = \Phi_I\left(\frac{I_t}{I_{t-1}}\right)I_t = \frac{\kappa}{2}\left(\frac{I_t}{I_{t-1}} - \mu^i\right)^2 I_t,$$

where $\kappa > 0$, and μ^i stands for the steady-state growth rate of investment. It turns out that the capital adjustment costs specification described in (6) has a better fit, which is why we select it for our benchmark estimation. For a detailed analysis of the implications of assumptions about the functional form of capital/investment adjustment costs in estimated NDBC models, see Avdjiev (2011).

shock. Note that in a decentralized economy with a competitive investment sector, A_t would be the equilibrium price of a unit of the investment good expressed in units of the consumption good.

The competitive equilibrium allocation coincides with the solution to the social planner problem, which consists of choosing non-negative processes C_t, h_t, u_t, I_t, and K_{t+1} in order to maximize (1) subject to (2)–(7). Following Schmitt-Grohe and Uribe (2008), we let $\Lambda_t Q_t$ and Λ_t denote the Lagrange multipliers on (4) and (7) respectively.

The first-order conditions for C_t, h_t, u_t, I_t and K_{t+1} are:

$$\Lambda_t = (C_t - \theta_c C_{t-1})^{-\gamma}(l_t - \theta_l l_{t-1})^{\chi(1-\gamma)} - \theta_c \beta E_t (C_{t+1} - \theta_c C_t)^{-\gamma}(l_{t+1} - \theta_l l_t)^{\chi(1-\gamma)} \tag{8}$$

$$\Lambda_t\big[Z_t X_t F_2(u_t K_t, X_t h_t)\big] = \left\{ \begin{array}{l} \chi(C_t - \theta_c C_{t-1})^{1-\gamma}(l_t - \theta_l l_{t-1})^{\chi(1-\gamma)-1} \\ \quad - \beta\theta_l \chi E_t[(C_{t+1} - \theta_c C_t)^{1-\gamma}(l_{t+1} - \theta_l l_t)^{\chi(1-\gamma)-1}] \end{array} \right\} \tag{9}$$

$$Z_t F_1(u_t K_t, X_t h_t) = Q_t \delta'(u_t) \tag{10}$$

$$Q_t = \frac{A_t}{\Omega_t[1 - \Phi_C'(\frac{I_t}{K_t})]}, \tag{11}$$

$$Q_t \Lambda_t = \beta E_t \Lambda_{t+1} \left[\begin{array}{l} Q_{t+1}[1 - \delta(u_{t+1}) + \Omega_{t+1}\{\frac{I_{t+1}}{K_{t+1}}\Phi_C'(\frac{I_{t+1}}{K_{t+1}}) - \Phi_C(\frac{I_{t+1}}{K_{t+1}})\}] \\ + Z_{t+1} u_{t+1} F_1(u_{t+1} K_{t+1}, X_{t+1} h_{t+1}) \end{array} \right]. \tag{12}$$

As result, the first-order conditions associated with the social planner's problem are given by (2)–(12).

Next, we turn to the asset pricing implications of the model. The one-period ahead gross real risk-free rate in the economy is given by:

$$R_t^{rf} = \frac{1}{\beta}\left[\frac{\Lambda_t}{E_t(\Lambda_{t+1})}\right]. \tag{13}$$

Combining the solutions to the problems solved by the representative agent and by the representative firm in a decentralized economy, we obtain the well-known expression for the equilibrium ex-dividend value (V_t) of the representative firm:

$$V_t = \beta E_t\left(\frac{\Lambda_{t+1}}{\Lambda_t}\right)(V_{t+1} + D_{t+1}), \tag{14}$$

where D_{t+1} is the dividend that the representative firm pays to its shareholders in period $t+1$. It is equal to the output produced by the firm during the period minus payments to labor and investment:

$$D_t = Y_t - W_t h_t - I_t A_t, \tag{15}$$

where W_t is the real wage in period t. The firm's first-order conditions imply that, in equilibrium, W_t is equal to the marginal product of labor (MPL):

$$W_t = MPL_t = (1-\alpha)\frac{Y_t}{h_t}, \tag{16}$$

where the second equality is implied by the assumption that the production function (3) has a Cobb–Douglas form. Inserting (16) in (15), we get:

$$D_t = \alpha Y_t - I_t A_t. \tag{17}$$

In turn, substituting (17) into (14) allows us to rewrite the expression for the end-of period value of the firm as:

$$V_t = \beta E_t\left(\frac{\Lambda_{t+1}}{\Lambda_t}\right)(V_{t+1} + \alpha Y_{t+1} - I_{t+1} A_{t+1}). \tag{18}$$

Iterating (18) forward, we obtain:

$$V_t = \sum_{i=1}^{\infty} E_t\left\{\beta^i\left(\frac{\Lambda_{t+i}}{\Lambda_t}\right)(\alpha Y_{t+i} - I_{t+i} A_{t+i})\right\}. \tag{19}$$

Eq. (19) states that the ex-dividend value of the firm is equal to the sum of the present values of its expected future dividends. Note that the expected future dividends of the representative firm are discounted using the representative household's intertemporal marginal rate of substitution (i.e. $\beta^i \frac{\Lambda_{t+i}}{\Lambda_t}$). This is due to the fact that households are assumed to be the ultimate owners of the firms in the economy.

2.2. Structure of the exogenous driving processes

The model is driven by four exogenous shock processes – a labor augmenting technology (LAT) shock, X_t; an investment-specific productivity (ISP) shock, A_t; a total factor productivity (TFP) shock, Z_t; and a marginal efficiency of investment (MEI) shock, Ω_t. Following Schmitt-Grohe and Uribe (2012), we assume that the first two processes are non-stationary, while the last two are stationary. We also assume that each of the four exogenous processes is subject to both, unanticipated innovations and anticipated innovations (i.e. news shocks). While we model unanticipated innovations in a conventional way, we examine two alternative specifications for the structure of the processes which guide the evolution of anticipated innovations.

The first specification that we explore, the short-run news (SRN) specification, is one that has now become standard in the NDBC literature (Davis, 2007; Khan and Tsoukalas, 2010; Schmitt-Grohe and Uribe, 2012; Fujiwara et al., 2011). It is given by:

$$\nu_t = \rho_\nu^s(\nu_{t-1}) + \epsilon_{\nu,t}^0 + \epsilon_{\nu,t-1}^1 + \epsilon_{\nu,t-2}^2 + \epsilon_{\nu,t-3}^3,$$

where $0 < \rho_\nu^s < 1$; $\nu_t = \widehat{\mu_{x,t}}, \widehat{\mu_{a,t}}, z_t, \omega_t$ denotes the deviation of the respective exogenous shock process from its steady state value in period t; the evolution of the two non-stationary shock processes (i.e. the LAT and the ISP shock processes) is defined relative to their respective growth rates: $\widehat{\mu_{x,t}} \equiv \log(\mu_{x,t}/\overline{\mu_x})$, $\mu_{x,t} \equiv \frac{X_t}{X_{t-1}}$, $\widehat{\mu_{a,t}} \equiv \log(\mu_{a,t}/\overline{\mu_a})$, $\mu_{a,t} \equiv \frac{A_t}{A_{t-1}}$, and $\overline{\mu_x}$ and $\overline{\mu_a}$ denote steady state values of the two shock processes' growth rates, $\mu_{x,t}$ and $\mu_{a,t}$, respectively; the evolution of the two stationary shock processes (i.e. the TFP and the MEI shock processes) is defined relative to their respective levels: $z_t \equiv \log(Z_t)$, $\omega_t \equiv \log(\Omega_t)$. Furthermore, $\epsilon_{\nu,t-j}^j$ (for $j = 0, 1, 2, 3$) denotes a change in the level of ν_t that materializes in period t, but enters the representative agent's information set in period $t - j$. When $j \neq 0$ (i.e. when the change in the level of ν_t enters the representative agent's information set before it materializes), one can think of $\epsilon_{\nu,t-j}^j$ as a news shock. By contrast, when $j = 0$, $\epsilon_{\nu,t}^j$ represents a conventional unanticipated shock – a shock that appears in the information set of the representative agent in the period in which it occurs. Finally, we make the following assumptions about the distributional properties of the model's exogenous shocks: $\epsilon_{\nu,t}^j \sim N(0, \sigma_{\nu,j}^2)$; $E\epsilon_{\nu,t}^j \epsilon_{\nu,t-m}^k = 0$ for $k, j = 0, 1, 2, 3$ and $m > 0$; $E\epsilon_{\nu,t}^j \epsilon_{\nu,t}^k = 0$ for any $k \neq j$.

The second specification that we examine, the long-run news (LRN) specification, was originally introduced by Cochrane (1994), but has so far not been explored in an estimated structural NDBC model. In it, the shock process evolves according to the following law of motion:

$$\nu_t = \rho_\nu^l(\nu_{t-1}) + \left(1 - \rho_\nu^l\right)\left(\nu_{t-1}^{LR}\right) + \epsilon_{\nu,t}^u,$$

where $0 < \rho_\nu^l < 1$, $\epsilon_{\nu,t}^u$ is an i.i.d. (unanticipated) innovation to ν_t, and ν_t^{LR} is the long-run component of ν_t:

$$\nu_t^{LR} = \left(\rho_\nu^{LR}\right)\left(\nu_{t-1}^{LR}\right) + \epsilon_{\nu,t}^{LR},$$

where $0 < \rho_\nu^{LR} < 1$ and $\epsilon_{\nu,t}^{LR}$ is an i.i.d. innovation to ν_t^{LR}. We make the following assumptions about the distributional properties of the model's exogenous shocks: $\epsilon_{\nu,t}^u \sim N(0, \sigma_{\nu,u}^2)$; $\epsilon_{\nu,t}^{LR} \sim N(0, \sigma_{\nu,LR}^2)$; $E\epsilon_{\nu,t}^u \epsilon_{\nu,t-m}^{LR} = 0$ for all m. The parameter ρ_ν^{LR} governs the degree of persistence in ν_t^{LR}, while ρ_ν^l determines the speed with which ν_t converges to its long-run component, ν_t^{LR}.[4] The higher ρ_ν^l is, the slower ν_t converges to ν_t^{LR} and vice versa. Note that agents learn about the innovation $\epsilon_{\nu,t}^u$ in the period in which it impacts the exogenous process, ν_t. In that sense, it directly corresponds to the unanticipated shock, $\epsilon_{\nu,t}^0$, in the SRN specification. By contrast, the innovation $\epsilon_{\nu,t}^{LR}$ does not affect the level of ν_t in period t, even though agents learn about it in that period. As a result, $\epsilon_{\nu,t}^{LR}$ can be thought of as a news shock.

Even though the number of possible news shock structures is infinite, we choose to focus on a single alternative specification for two main reasons. The first reason is practical – it would be impossible to present the results for a large number of alternative specifications in a single paper. The second reason is related to the fact that asking the model to fit data on asset prices is a crucial part of our empirical exercise. As demonstrated by the long-run risks strand of the asset pricing literature (Bansal and Yaron, 2004; Piazzesi and Schneider, 2007; Hansen et al., 2008; Eraker and Shaliastovich, 2008; Bansal et al., 2010; Drechsler and Yaron, 2011, etc.), modeling the exogenous shock processes as containing small long-run predictable components can help explain key asset pricing phenomena. This motivates us to focus on a news shock specification which implies that the exogenous processes in our model have a slow-moving long-run component.

Fig. 1 presents the impulse responses of a generic stochastic process to the three types of shocks discussed above. Note that the shape of the impulse response to a short-run news shock is very similar to that of the impulse response to an unanticipated shock, except for the fact that it is shifted to the right by j periods (i.e. the shock affects the exogenous process with a delay of j periods).[5] By contrast, the impulse response to a long-run news shock looks very different from the other two impulse responses. Namely, due to the fact that it affects the long-run component of the exogenous process, its impact gradually increases in magnitude over time.

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[4] For each of the four exogenous processes, we estimate ρ_ν^l and we set the value of ρ_ν^{LR} to 0.999, so that it is very persistent, yet stationary.

[5] The example in Fig. 1 assumes $j = 3$.

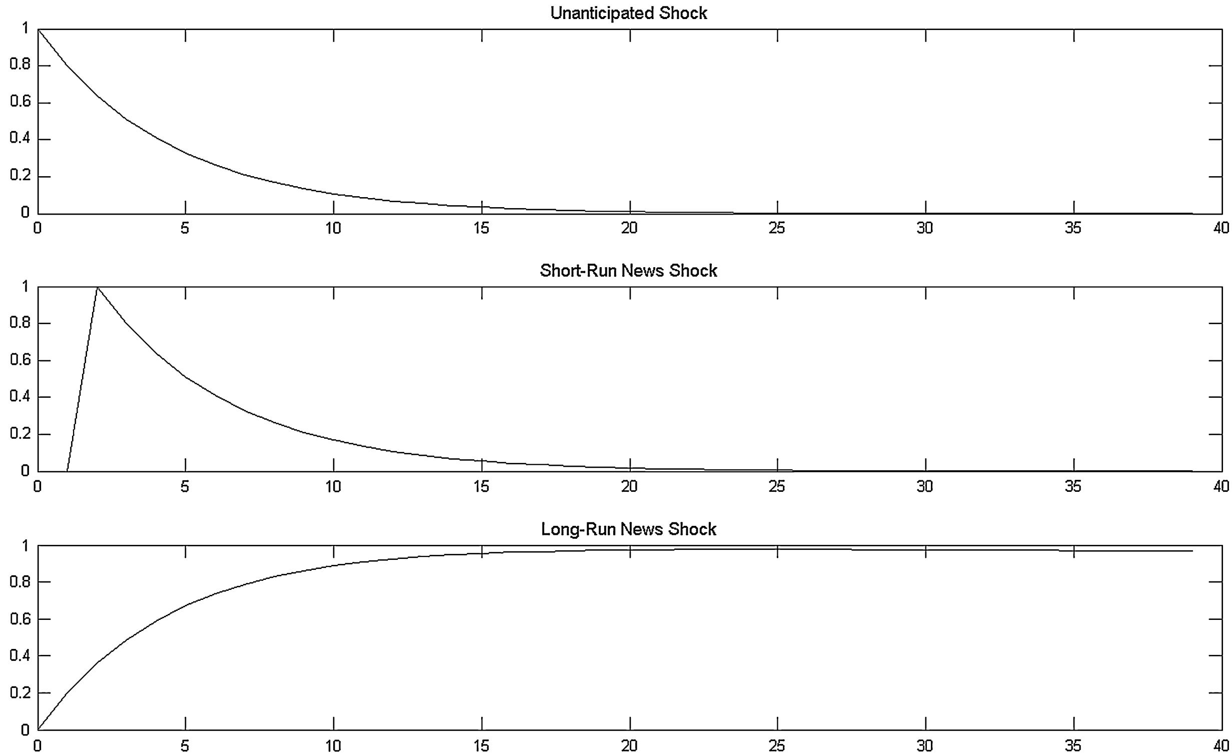


Fig. 1. Impulse response functions of a generic stochastic process to the three types of shocks studied in the paper.

3. Bayesian inference

We use Bayesian Markov Chain Monte Carlo (MCMC) methods in order to obtain estimates of the posterior distributions of the non-calibrated structural parameters (Θ) and the unobserved states (S_t, $t = 1, \ldots, T$) of the state space model.[6] In particular, following a methodology similar to the one described in An and Schorfheide (2007), we employ a combination of the Random Walk Metropolis–Hastings (RWMH) and the Gibbs Sampling (GS) algorithms in order to consecutively sample from the conditional distributions of the unknown parameters and the unobserved states.[7]

We estimate each of the two model specifications using a vector of observable variables (O_t) that includes five macroeconomic variables (real output growth, real consumption growth, real investment growth, hours worked, and the growth rate of the relative price of investment) and two asset price variables (total stock market valuation and the three-month real risk-free interest rate). More specifically, the vector of observable variables is given by:

$$O_t = \begin{bmatrix} \Delta\log(Y_t) \\ \Delta\log(C_t) \\ \Delta\log(A_t I_t) \\ \log(h_t) \\ \Delta\log(A_t) \\ \Delta\log(V_t) \\ \log(R_t^{RF}) \end{bmatrix}, \tag{20}$$

where $\Delta\log(Y_t)$ is the log of the gross growth rate of real GDP per capita, $\Delta\log(C_t)$ is the log of the gross growth rate of real per capita consumption, $\Delta\log(A_t I_t)$ is the log of the gross growth rate of real per capita investment, $\log(h_t)$ is the log of total hours worked, $\Delta\log(A_t)$ is the log of the gross growth rate of the relative price of investment, $\Delta\log(V_t)$ is the log of the gross growth rate of total market valuation for the US stock market, and $\log(R_t^{RF})$ is the log of the gross real three-month risk-free interest rate. We use quarterly US data from 1951:Q1 to 2009:Q4.[8] As discussed in the Introduction, we follow the approach of Justiniano et al. (2013) and assume that each of the two asset price series has a normally

[6] The methodology used to solve the model and obtain its state space representation is described in Appendix A.

[7] We present a detailed description of the steps involved in the Bayesian MCMC algorithm that we use to estimate the model in Appendix B.

[8] Appendix C provides a detailed description of the data that we use in order to obtain the observable variables listed above.

Table 1
Calibrated parameters.

Parameter	Value
β	0.9966
α	0.30
ρ_x^{LR}	0.999
ρ_a^{LR}	0.999
ρ_z^{LR}	0.999
ρ_ω^{LR}	0.999
$\overline{\mu_a}$	0.9982
$\overline{\mu_y}$	1.0044
δ_0	0.025
$\bar{h}$	0.20
$\bar{u}$	1.00
$\bar{Z}$	1.00
$\overline{\Omega}$	1.00

distributed, zero-mean measurement error associated with it. We denote the standard deviations of these measurement errors by $\sigma_{O,J}$ $(J = V, R)$.

We fix a small number of parameters to values that are implied by the steady state conditions of our model or are commonly used in the literature. All calibrated parameters are summarized in Table 1.

We estimate the rest of the model's parameters. The prior distributions for all estimated parameters in each of the four model specifications that we examine are summarized in Tables D.1 and D.2 in Appendix D. In general, unless there is a solid theoretical reason for not doing so, we impose fairly flat (uninformative) priors in order to let the data (i.e. the likelihood function) have as much weight as possible in determining the posterior distributions.

In order to "level the playing field" for the SRN and the LRN specifications as much as possible, we choose the same prior means for the standard deviations of the unanticipated innovations to each of the four exogenous driving processes in the two specifications (i.e. $\sigma_{\nu,0} = \sigma_{\nu,u}$ for $\nu = x, a, z, \omega$). We incorporate our prior information about the relative sizes of the long-run components in the LRN specification by assigning values for the prior means of the standard deviations of the innovations to these components that are five times smaller than the values for the prior means of the standard deviations of the unanticipated innovations.[9] Finally, as discussed in the Introduction, we restrict the standard deviation of the measurement errors in the two asset prices used in the estimation (i.e. total market valuation and the real risk-free interest rate) to be at most 30% of the unconditional standard deviation of the corresponding observable variable. In imposing the latter restriction we are following the approach of Schmitt-Grohe and Uribe (2012), who allow for a measurement error in output growth and impose an upper bound on its prior distribution, which is a function of the standard deviation of the corresponding observable variable.

4. Comparing the performance of the SRN and the LRN model specifications

The variance decompositions for the SRN and the LRN model specifications are displayed in Tables 2 and 3, respectively.[10] There are several important differences between the two sets of variance decompositions.

First, the structural form of the news shock processes has a significant impact on inference about the main drivers of fluctuations in stock prices. When the LRN specification is assumed, the main driver of stock prices is the ISP news shock. By contrast, under the SRN specification, stock prices are primarily driven by the unanticipated MEI shock.

Second, inference about the main drivers of the real risk-free interest rate is also very sensitive to assumptions about the structure of the news shock processes. In the LRN model specification, this variable is primarily driven by the unanticipated TFP shock and the TFP news shock. Meanwhile, the estimates from the SRN model specification imply that the main drivers of fluctuations in the real risk-free interest rate are the unanticipated LAT and the unanticipated MEI shocks.

Finally, there are important differences between the variance decompositions of macroeconomic variables implied by the two alternative model specifications. For example, when long-run news shocks are assumed, the majority of fluctuations in consumption growth are driven by the unanticipated TFP shock. By contrast, the under the assumption of short-run news shocks, the unanticipated MEI shock is the leading driver of the same variable. Furthermore, the share of the variance explained by the latter shock is considerably higher in the SRN specification than in the LRN specification for all other macroeconomic variables.

[9] Our prior information is based on the findings of the long-run risks literature (Bansal and Yaron, 2004; Croce, 2008; Avdjiev and Balke, 2010).

[10] The variance decompositions in Tables 2 and 3 are obtained using the vector of observables presented in (20). The variance decompositions obtained when the SRN and the LRN model specifications are estimated without using data on asset prices (i.e. using only data on macroeconomic variables) are displayed in Tables D.3 and D.4, respectively, in Appendix D.

Table 2
Posterior variance decompositions at business cycle horizons in the SRN model specification.

Series\shock	Unanticipated LAT	News LAT	Unanticipated ISP	News ISP	Unanticipated TFP	News TFP	Unanticipated MEI	News MEI
Output growth	0.19	0.05	0.01	0.00	0.42	0.02	0.28	0.02
Consumption growth	0.17	0.03	0.01	0.00	0.23	0.01	0.45	0.09
Investment growth	0.07	0.03	0.00	0.00	0.03	0.00	0.76	0.10
Hours	0.31	0.06	0.04	0.00	0.06	0.00	0.49	0.03
Relative price of investment	0.00	0.00	0.97	0.03	0.00	0.00	0.00	0.00
Total market valuation	0.13	0.04	0.00	0.00	0.05	0.00	0.73	0.04
Real risk-free interest rate	0.41	0.12	0.00	0.00	0.00	0.02	0.24	0.21

Note: SRN = short run news shocks, LAT = labor augmenting technology, ISP = investment-specific productivity, TFP = total factor productivity, MEI = marginal efficiency of investment. Each set of variance decompositions corresponds to medians based on 100 000 draws from the posterior distribution obtained using the Random Walk Metropolis–Hastings algorithm as described in Appendix B. Unlike means, medians need not add up to one. The entries in each of the four (short run) news shock columns represent the sums of the variance decomposition shares attributed to the three anticipated (one, two, and three periods ahead) innovations to the respective shock. Business cycle horizons = 6 to 32 quarters.

Table 3
Posterior variance decompositions at business cycle horizons in the LRN model specification.

Series\shock	Unanticipated LAT	News LAT	Unanticipated ISP	News ISP	Unanticipated TFP	News TFP	Unanticipated MEI	News MEI
Output growth	0.10	0.00	0.04	0.03	0.51	0.20	0.11	0.00
Consumption growth	0.08	0.00	0.01	0.02	0.60	0.22	0.07	0.00
Investment growth	0.02	0.00	0.05	0.34	0.01	0.06	0.51	0.01
Hours	0.07	0.01	0.21	0.05	0.01	0.28	0.38	0.00
Relative price of investment	0.00	0.00	0.79	0.21	0.00	0.00	0.00	0.00
Total market valuation	0.04	0.00	0.02	0.70	0.02	0.14	0.08	0.00
Real risk-free interest rate	0.00	0.00	0.01	0.04	0.54	0.35	0.07	0.00

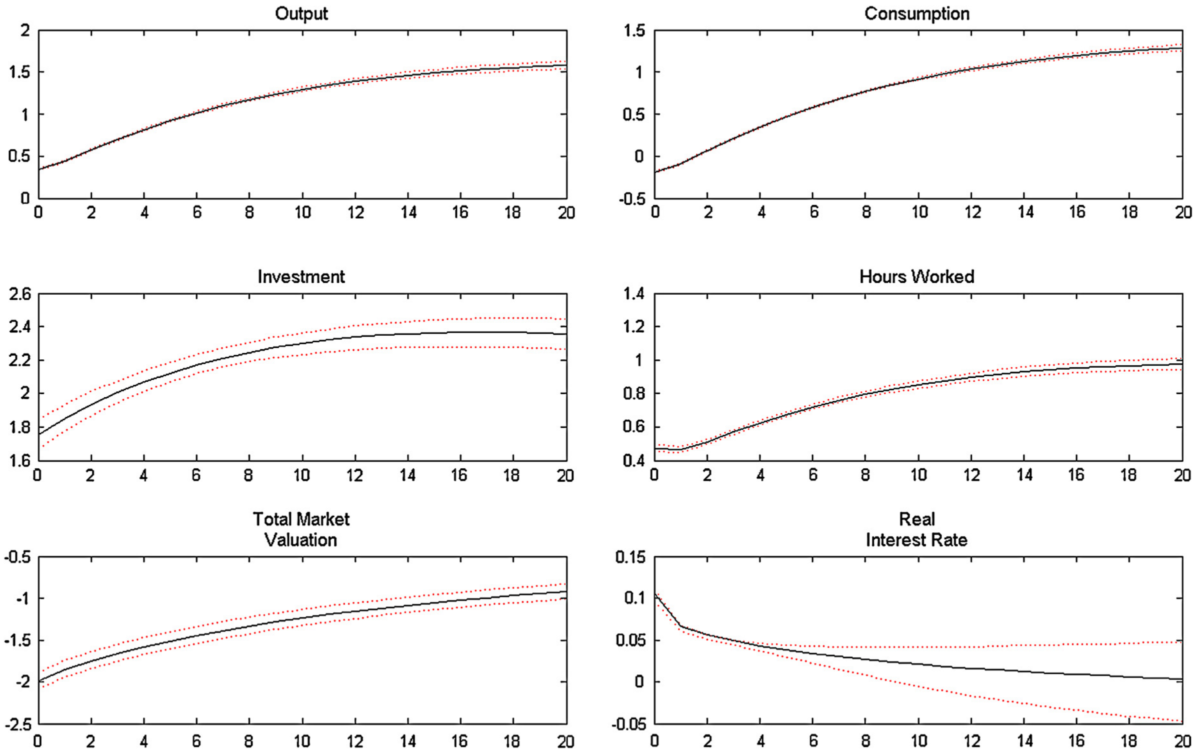
Note: LRN = long run news shocks, LAT = labor augmenting technology, ISP = investment-specific productivity, TFP = total factor productivity, MEI = marginal efficiency of investment. Each set of variance decompositions corresponds to medians based on 100 000 draws from the posterior distribution obtained using the Random Walk Metropolis–Hastings algorithm as described in Appendix B. Unlike means, medians need not add up to one. Business cycle horizons = 6 to 32 quarters.

The above results illustrate that conclusions about the main drivers of fluctuations in macroeconomic variables and asset prices are very sensitive to assumptions about the structure of the news shock processes. As a result, in order to make a definitive statement about the main drivers, we need to determine which of the two model specifications has a better fit. In order to do that, we calculate and compare their log marginal likelihoods.

It turns out that the LRN model specification has a higher log marginal likelihood (−9461.8) than the SRN model specification (−9562.1). This suggests that, when a structural NDBC model is estimated using asset prices in addition to macroeconomic variables as observables, the data favors long-run news shocks over the traditional short-run news shocks. This result stands in sharp contrast to the benchmark assumptions about the news shock processes in the existing literature on structural NDBC models (Davis, 2007; Khan and Tsoukalas, 2010; Fujiwara et al., 2011; Schmitt-Grohe and Uribe, 2012).

The LRN specification outperforms the SRN specification mainly due to the ability of the long-run ISP news shock to drive a wedge between the volatility of macroeconomic variables and short-term interest rates, on the one side, and the value of the firm, on the other side. In the data, the growth rate of total market valuation is a lot more volatile than each of the macroeconomic variables used in the estimation – its standard deviation (8.74%) is almost four times larger than that of investment growth (2.56%), more than nine times larger than that of output growth (0.95%), and approximately 16 times larger than that of consumption growth (0.55%). In addition, its standard deviation is more than 15 times larger than that of the short-term real interest rate (0.58%). As a result, in order for a model specification to be able to simultaneously fit all of those series, it must generate shocks that not only trigger a positive comovement among the key endogenous variables of the model (i.e. match the qualitative features of the data), but also create a wedge between the scale of variation in macroeconomic variables and short-term interest rates, on the one side, and stock prices, on the other side (i.e. match the quantitative features of the data). While both model specifications examined in this paper contain at least one shock that satisfies the former condition, the latter one turns out to be elusive for the SRN specification.

By construction, the SRN specification has two groups of shocks to select from – unanticipated shocks and short-run news shocks. An unanticipated shock is not able to create a wedge between the degree of variability in macroeconomic variables and short-term interest rates and that in stock prices due to the fact that it fails to generate the persistence in the dividend process that is needed to do that (19). Short-run news shocks suffer from the same problem since, by design, the structure of their dynamics is identical to that of unanticipated shocks, save for the fact that they are delayed by one, two, or three periods (Fig. 1). As a result, any shock that belongs to one of the above two groups and causes sufficiently small responses in macroeconomic variables and short-term interest rates to be able to successfully match the



Note: MEI = marginal efficiency of investment. The solid line is the median; the dotted lines are the 5th and the 95th percentiles.

Fig. 2. Impulse responses to a one-standard-deviation *unanticipated MEI* shock in the LRN model specification.

data, fails to generate large enough fluctuations in total market valuation. Alternatively, if such a shock triggers adequately large fluctuations in total market valuation, it also causes implausibly large responses in macroeconomic aggregates.

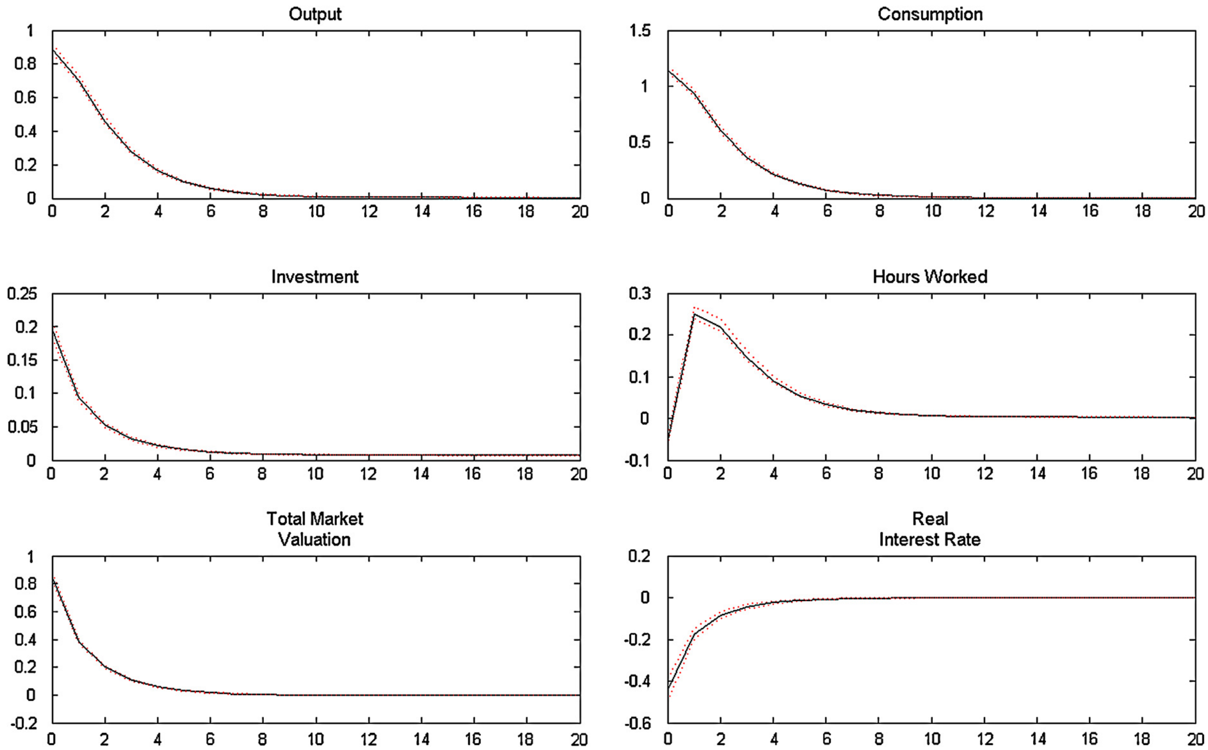
By contrast, the inherent persistence of a long-run news shock allows it to create the quantitative wedge between macroeconomic variables and stock prices that the other two groups of shocks fail to generate. This is possible due to the combination of two facts. First, the impact of a long-run news shock on the determinants of the representative firm's dividends extends many periods into the future (19). Second, stock prices are both, forward-looking and much more flexible than macroeconomic variables. As a result, long-run news shocks that are small enough in magnitude to have a realistic impact on macroeconomic aggregates are also able to trigger a sufficiently large response in the value of the firm.

5. The main drivers of fluctuations in the LRN specification

The results from the LRN specification suggest that the main drivers of fluctuation in macroeconomic variables are the unanticipated TFP shock and the unanticipated MEI shock. The former shock accounts for more than half of the variances of output (51%) and consumption (60%). The latter shock explains 51% of the fluctuations in investment growth and 38% of those in hours. The importance of these shocks can largely be attributed to their ability to trigger a positive comovement among the four macroeconomic variables, which corresponds to the comovement observed in the data (Figs. 2 and 3).

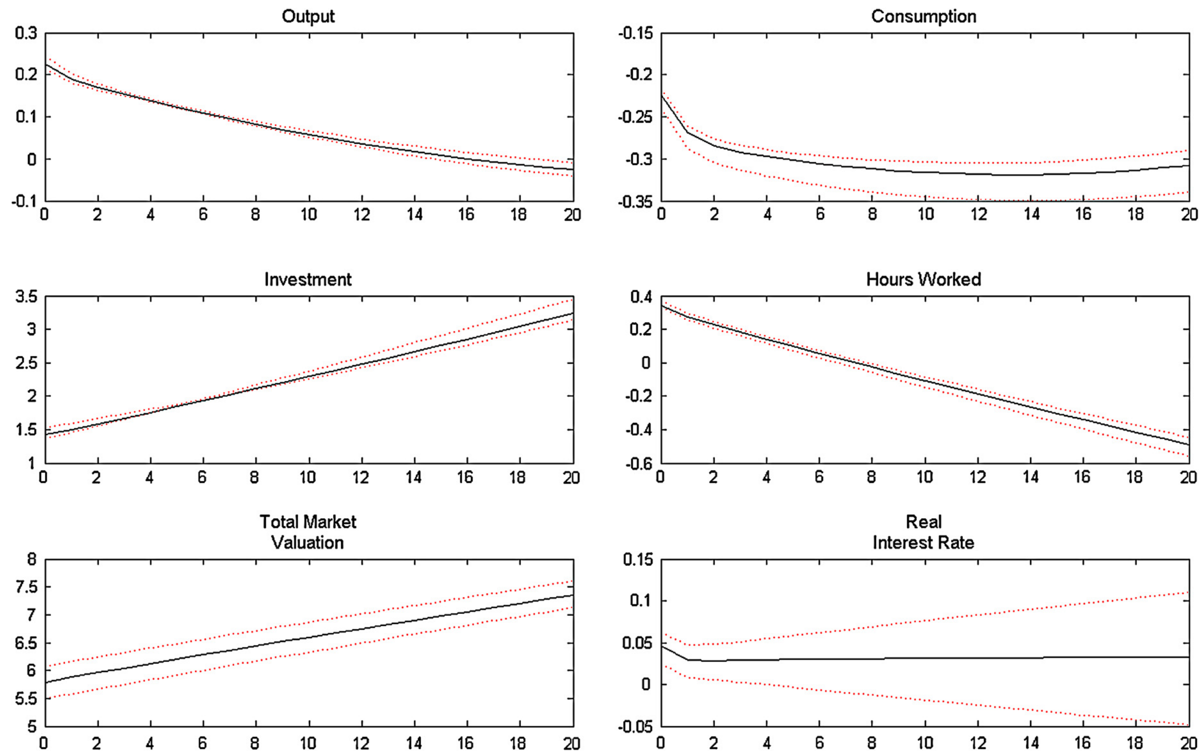
Despite being the main drivers of fluctuations in macroeconomic variables, neither of the above two shocks is assigned a major share of the variance of stock prices. This result is explained by their inability to generate a response in the value of the firm that has both, the right sign and the right magnitude. More specifically, a positive unanticipated MEI shock generates a negative response in the value of the firm (Fig. 2). This occurs mainly due to the fact that it causes a rightward shift in the supply of capital (induced by the lower level of adjustment costs per unit of investment) that is greater in magnitude than the rightward shift in the demand for capital (caused by the fact that capital becomes more valuable as a tool for mitigating the adjustment costs associated with the expected higher future levels of investment) triggered by the same shock. Meanwhile, a positive unanticipated TFP shock does generate a positive response in the value of the firm (Fig. 3). However, the magnitude of that response is not sufficient to allow the unanticipated TFP shock to explain a major part of the fluctuations in stock prices.

With the unanticipated MEI shock and the unanticipated TFP shock incapable of generating a positive response in the value of the firm, the ISP news shock emerges as the main driver of fluctuations in total market valuation, explaining more than two thirds (70%) of its variation at business cycle frequencies. A positive ISP news shock (i.e. a shock that reduces the relative price of investment) generates a large positive response in the value of the firm (Fig. 4). It shifts the demand for capital to the right due to the fact that capital becomes more valuable as a tool for mitigating the adjustment costs



Note: TFP = total factor productivity. The solid line is the median; the dotted lines are the 5th and the 95th percentiles.

Fig. 3. Impulse responses to a one-standard-deviation *unanticipated TFP* shock in the LRN model specification.



Note: ISP = investment-specific productivity. The solid line is the median; the dotted lines are the 5th and the 95th percentiles.

Fig. 4. Impulse responses to a one-standard-deviation *ISP news* shock in the LRN model specification.

Table 4
Share of variance explained by news shocks in the LRN model specification.

Percentile	Output growth	Consumption growth	Investment growth	Hours	Total market valuation	Real risk-free interest rate
5th	22.6	22.8	38.7	31.2	82.5	38.1
50th	23.5	23.7	40.9	32.9	83.9	38.7
95th	24.3	24.3	43.1	36.2	85.4	39.2

Note: Shares are in percent.

associated with the higher levels of investment. Qualitatively, this shift in the demand for capital is identical to the one generated by the unanticipated MEI shock described above. Quantitatively, however, it is much larger.

Intuitively, the persistence of the long-run ISP news shock leads agents to rationally expect a prolonged period of rising investment, which, in turn, makes capital more valuable as a mitigant for the associated increase in capital adjustment costs. This effect is weaker in the case of an unanticipated MEI shock, which is not as persistent and, as a result, the increase in investment growth that it generates is not nearly as long-lived as the one triggered by the ISP news shock. The contemporaneous increase in the price of capital is further enhanced by the fact that, in contrast to what occurs in the case of an unanticipated MEI shock, the supply of capital does not shift immediately since the level of ISP remains unchanged in the period in which the ISP news shock occurs.

Table 4 displays the share of the variance decompositions of the observable variables attributed to news shocks in the LRN specification. News shocks are not the major driver of fluctuations for any of the macroeconomic variables that we examine. They are responsible for less than a quarter of the fluctuations in output and consumption and for less than a third of those in hours. The macroeconomic variable for which their estimated variance share is the largest is investment. However, even in that case they are not the major driver of fluctuations, accounting for roughly 40%. Nevertheless, news shocks are the primary driver of total market valuation. As a group, they explain 84% of the variance of that variable.

The above estimates of the share of macroeconomic fluctuations attributable to news shocks are considerably lower than those implied by the results of the rest of the literature on estimated structural NDBC models. For example, Schmitt-Grohe and Uribe (2012) conclude that news shock account for approximately half of the fluctuations in macroeconomic variables.

The main reason due to which the results in the existing literature differ considerably from ours is related to the assumptions made about the structure of the news shock processes. Namely, virtually all papers in the rest of the literature on estimated structural NDBC models focus exclusively on the SRN specification. However, it turns out that the alternative long-run news specification that we consider has a better fit when the model is estimated using data on asset prices and macroeconomic variables. The results implied by that model specification suggest that, while news shocks are a major driver of aggregate stock market fluctuations, their share of the variance decompositions of macroeconomic variables is considerably less than half.

Intuitively, the inclusion of the two asset price variables in the vector of observables affects the results by imposing additional discipline on the estimation. More specifically, it introduces two new restrictions, (13) and (19), which affect inference about the leading sources of business cycle fluctuations through their impact on the identification of the unobserved shocks. When the set of observable variables is augmented by the inclusion of asset prices, the number of model-implied relationships that the unobserved shocks have to satisfy increases. As a result, some of the shocks that the model uses to fit the data which consist solely of macroeconomic variables no longer satisfy the enhanced set of model-implied relationships. This causes the estimated importance of such shocks in driving economic fluctuations to diminish significantly once asset prices are taken into consideration. The shocks that emerge to replace them tend to be those that have more realistic implications for the joint behavior of macroeconomic aggregates and asset prices, even if they are slightly dominated by the former group of shocks in terms of their implications for the stand-alone behavior of macroeconomic variables.

6. Conclusion

In this paper, we demonstrate that inference from estimated structural NDBC models about the main sources of fluctuations in macroeconomic variables and asset prices is sensitive to assumptions about the structure of the news shock processes. Our results indicate that the structural form of the news shock processes has a significant impact on inference about the main drivers of fluctuations in the aggregate stock market and the real risk-free interest rate. Furthermore, there are important differences between the variance decompositions of macroeconomic variables implied by the two alternative specifications.

Our results also have important implications for the structural form of the news shock processes. They reveal that, when data on asset prices are used in the estimation of a structural NDBC model, the LRN specification is preferred by the data over the SRN specification assumed throughout the existing NDBC literature.

Finally, according to the results from the LRN model specification, long-run news shocks account for less than a quarter of the fluctuations in output and consumption and for less than a third of those in hours. Nevertheless, the same set of estimates suggests that long-run news shocks are a major driver of fluctuations in aggregate stock prices, accounting for 84% of the variance of that series.

The paper presents several possible directions for future research. First, it would be intriguing to augment the model presented in this paper with features, such as Epstein–Zin preferences (Epstein and Zin, 1989), long-run risks, or time-varying volatility, that have been shown to improve the empirical performance of asset pricing models. This could enhance the ability of the benchmark model to match the data on asset prices, and, in doing so, bring in new information about the importance of news shocks and unanticipated shocks in driving macroeconomic fluctuations. The usefulness of such an exercise would be greatly enhanced if it takes advantage of information on second moments by adopting a second-order approximation of the solution and a particle filter to evaluate the likelihood function as in Fernandez-Villaverde and Rubio-Ramirez (2007). Second, it would also be worth exploring whether the main results of the paper extend beyond the RBC framework that we focus on. More precisely, it would be interesting to examine whether inference about the main drivers of business cycle fluctuations is robust to assumptions about the nature of the news shock processes in a New Keynesian setting. Finally, it would be interesting to examine how the results presented in this paper would be affected by the introduction of a financial sector as in Christiano et al. (2010). As pointed out by Justiniano et al. (2011), one can broadly think of MEI shocks as proxies for shocks to the efficiency of the financial intermediation process in the economy. Since we estimate MEI shocks to be among the main sources of business cycle fluctuations in the model specification with the best fit, we believe that incorporating financial intermediation into the theoretical environment of this paper would be a worthwhile endeavor.

Appendix A. Solution method

Two of the four exogenous driving processes (X_t and A_t) have stochastic trends. As a result, all of the endogenous variables in the model, with the exception of hours worked (h_t), leisure (l_t), and capacity utilization (u_t), fluctuate around a stochastic balanced growth path. In order to induce stationarity to the system, we divide each endogenous variable which has a unit root by its trend component. The stochastic trend component of output is given by $X_t^Y = A_t^{\alpha/(\alpha-1)} X_t$. The stochastic trend component of capital is given by $X_t^K = A_t^{1/(\alpha-1)} X_t$. We define the following stationary variables: $\widetilde{y}_t = \frac{Y_t}{X_t^Y}$, $\widetilde{k}_t = \frac{K_t}{X_{t-1}^K}$, $\widetilde{c}_t = \frac{C_t}{X_t^Y}$, $\widetilde{i}_t = \frac{I_t}{X_t^K}$, $\widetilde{q}_t = \frac{Q_t}{A_t}$, $\widetilde{v}_t = \frac{V_t}{X_t^Y}$, $\widetilde{\lambda}_t = \frac{\Lambda_t}{(X_t^Y)^{-\sigma}}$. Let the growth rates of the trends in output and capital be given by:

$$\mu_t^y = \frac{X_t^Y}{X_{t-1}^Y},$$

$$\mu_t^k = \frac{X_t^K}{X_{t-1}^K}.$$

Using the above notation, we can write the balanced growth path of the economy as:

$$\widetilde{c}_t + \widetilde{i}_t = \widetilde{y}_t$$

$$\widetilde{y}_t = z_t F\left(\frac{u_t \widetilde{k}_t}{\mu_t^k}, h_t\right)$$

$$h_t + l_t = 1$$

$$\widetilde{k}_{t+1} = \big(1 - \delta(u_t)\big)\frac{\widetilde{k}_t}{\mu_t^k} + \widetilde{i}_t - \Phi\left(\frac{\widetilde{i}_t \mu_t^k}{\widetilde{k}_t}\right)\widetilde{k}_t$$

$$\widetilde{\lambda}_t = \left(\widetilde{c}_t - \theta_c \frac{\widetilde{c}_{t-1}}{\mu_t^y}\right)^{-\sigma} (l_t - \theta_l l_{t-1})^{\chi(1-\sigma)} - \theta_c \beta \big(\widetilde{c}_{t+1}\mu_{t+1}^y - \theta_c \widetilde{c}_t\big)^{-\sigma} (l_{t+1} - \theta_l l_t)^{\chi(1-\sigma)}$$

$$\widetilde{\lambda}_t z_t F_2\left(\frac{u_t \widetilde{k}_t}{\mu_t^k}, h_t\right) = \left\{ \begin{array}{l} \chi(\widetilde{c}_t - \theta_c \frac{\widetilde{c}_{t-1}}{\mu_t^y})^{1-\sigma} (l_t - \theta_l l_{t-1})^{\chi(1-\sigma)-1} \\ \quad - \theta_c \beta \chi (\widetilde{c}_{t+1}\mu_{t+1}^y - \theta_c \widetilde{c}_t)^{1-\sigma} (l_{t+1} - \theta_l l_t)^{\chi(1-\sigma)-1} \end{array} \right\}$$

$$z_t F_1\left(\frac{u_t \widetilde{k}_t}{\mu_t^k}, h_t\right) = \widetilde{q}_t \delta'(u_t)$$

$$\widetilde{q}_t = \frac{1}{1 - \Phi'(\frac{\widetilde{i}_t \mu_t^k}{\widetilde{k}_t})}$$

$$\widetilde{q}_t \widetilde{\lambda}_t = \beta E_t \mu_{t+1}^a (\mu_{t+1}^y)^{-\sigma} \widetilde{\lambda}_{t+1} \left\{ \begin{array}{l} [1 - \delta(u_{t+1}) - \Phi(\frac{\widetilde{i}_{t+1}\mu_{t+1}^k}{\widetilde{k}_{t+1}}) + \frac{\widetilde{i}_{t+1}\mu_{t+1}^k}{\widetilde{k}_{t+1}} \Phi'(\frac{\widetilde{i}_{t+1}\mu_{t+1}^k}{\widetilde{k}_{t+1}})]\widetilde{q}_{t+1} \\ \quad + z_{t+1} u_{t+1} F_1(\frac{u_{t+1}\widetilde{k}_{t+1}}{\mu_{t+1}^k}, h_{t+1}) \end{array} \right\}$$

$$\mu_t^y = (\mu_t^a)^{\alpha/(\alpha-1)} \mu_t^x$$

$$\mu_t^k = \left(\mu_t^a\right)^{1/(\alpha-1)} \mu_t^x$$
$$R_t^{rf} = \frac{1}{\beta} E_t\left(\frac{\widetilde{\lambda}_t}{\widetilde{\lambda}_{t+1}}\right)\left(\mu_{t+1}^y\right)^{\sigma}$$
$$\widetilde{v}_t = \beta E_t\left[\frac{\widetilde{\lambda}_{t+1}}{\widetilde{\lambda}_t}\left(\mu_{t+1}^y\right)^{1-\sigma}\right](\widetilde{v}_{t+1} + \alpha\widetilde{y}_{t+1} - \widetilde{i}_{t+1}).$$

Next, we compute the non-stochastic steady state of each of the two model specifications that we consider (i.e. the SRN and the LRN model specifications). We then log-linearize the stationary equilibrium conditions around the steady state. Finally, we solve the resulting system of linear rational expectation equations as in Blanchard and Kahn (1980) and Uhlig (1999) in order to obtain its state space representation:

$$O_t = A + \Psi S_t + V_t \tag{A.1}$$
$$S_t = G + F S_{t-1} + U_t, \tag{A.2}$$

where O_t is a vector of observable variables, S_t is a vector of unobserved states, $V_t \sim N(0, R)$ is a vector of measurement errors, $U_t \sim N(0, Q)$ is a vector of structural shocks, R is a diagonal matrix with the variances of the measurement errors on its main diagonal, and Q is a diagonal matrix with the variances of the structural shocks on its main diagonal. Note that the matrices A, G, Ψ, F, Q, and R are functions of the structural parameters of the model. We use the above state space model as the basis for our estimation procedure, which we describe in the next section.

Note that in the context of the state space model in (A.1) and (A.2), the exogenous shock processes, which are not directly observed, belong to the vector of unobserved states, S_t, and not to the vector of observable variables, O_t. Our exercise demonstrates that adding asset prices to the vector of observables, which is equivalent to imposing more restrictions (i.e. (13) and (19)) on the estimation of the state space model, has a significant impact on inference about the statistical properties and the actual realizations of the unobserved states (i.e. the unanticipated shocks and the news shocks) due to the fact that it unveils relevant information about the unobserved shock processes – information that cannot be obtained by using solely data on macroeconomic aggregates.

Appendix B. Bayesian estimation

Given the data, O_T, and the set of structural parameters, Θ, we obtain estimates of the conditional distributions of the unobserved states by using the Kalman Filter. Given the conditional distributions of the unobserved states, the predictive log-likelihood of the state space model is given by:

$$l(O_T, \Theta) = \sum_{t=1}^{T}\left\{\begin{array}{l} -0.5\log(\det(\Psi(\Theta)P_{t|t-1}\Psi(\Theta)' + R)) \\ \quad -0.5(O_T - \Psi(\Theta)S_{t|t-1} - A)'(\Psi(\Theta)P_{t|t-1}\Psi(\Theta)' + R)^{-1}(O_T - \Psi(\Theta)S_{t|t-1} - A) \end{array}\right\}, \tag{B.1}$$

where $S_{t|t-1}$ is the conditional mean and $P_{t|t-1}$ is the conditional variance of S_t, obtained from the Kalman Filter. Given the prior distribution of the vector of structural parameters, $\pi(\Theta)$, the posterior distribution, $P(\Theta|O_T)$, can be written as:

$$P(\Theta|O_T) \propto \left[\exp\left(l(O_T, \theta)\right)\right]\left[\pi(\theta)\right]. \tag{B.2}$$

It is not possible to obtain an analytical expression for the posterior distribution given in (B.2) because the log-likelihood (B.1) is a highly non-linear function of the vector of structural parameters, Θ. That is why we use Bayesian Markov Chain Monte Carlo (MCMC) methods in order to obtain estimates of the joint posterior distribution of the structural parameters and the unobserved states. Namely, we use a combination of the Random Walk Metropolis–Hastings (RWMH) and the Gibbs Sampling (GS) algorithms in the following way:

1. We choose arbitrary initial values for the structural parameters, $\Theta^{(0)}$, and for the unobserved states, $S^{(0)}$.

2. For $i = 1, \ldots, n_{sim}$, we use the Kalman Filter to obtain the conditional distributions of the unobserved states given $\Theta^{(i-1)}$: $P(S_T|\Theta^{(i-1)}, Y_T)$. We obtain a draw, $S_T^{(i)}$, from $P(S_T|\Theta^{(i-1)}, Y_T)$. In this step, we use the "filter forward, sample backward" approach proposed by Carter and Kohn (1994) and discussed in Kim and Nelson (1999).

3. Given $\Theta^{(i-1)}$, we draw a candidate set of parameters, $\Theta^{(c)}$, from a pre-specified distribution: $g(\Theta^{(c)}|\Theta^{(i-1)})$. In our application of the procedure, $g(\cdot)$ is such that, $\Theta^{(c)} = \Theta^{(i-1)} + v$, where v is drawn from a multivariate t-distribution with five degrees of freedom and a covariance matrix Σ. We set Σ to be a scaled version of the Hessian matrix of the log posterior probability, evaluated at the posterior mode. We choose the scale so that 20%–30% of the candidate draws are accepted.

4. We determine the acceptance probability, α, for the candidate draw:

$$\alpha\left(\Theta^{(c)}, \Theta^{(i-1)}\right) = \min\left\{\frac{[\exp(l(O_T, \Theta^{(c)}))][\pi(\Theta^{(c)})]}{[\exp(l(O_T, \Theta^{(i-1)}))][\pi(\Theta^{(i-1)})]}, 1\right\}.$$

5. We select $\Theta^{(i)}$ according to the following rule:

$\Theta^{(i)} = \Theta^{(c)}$ with probability α;

$\Theta^{(i)} = \Theta^{(i-1)}$ with probability $1-\alpha$.

6. If $i < n_{sim}$, we return to step 2. Once $i = n_{sim}$, we move on to step 7.

7. We discard the first m draws ($m < n_{sim}$) in order to ensure that the initial conditions do not influence our estimates in any way. We approximate the expected value of any function of interest, $f(\Theta)$, by using the following formula:

$$\widehat{f(\Theta)} = \left(\frac{1}{n_{sim} - m}\right) \sum_{i=m+1}^{n_{sim}} f\left(\Theta^{(i)}\right).$$

In this particular application, we run 500 000 iterations of the sampling procedure (i.e. we set $n_{sim} = 500\,000$) and we use the last 100 000 draws (i.e. $m = 400\,000$) to make inference about the posterior distributions of the structural parameters and the unobserved states.

Appendix C. Data sources

The data that we use is quarterly and runs from 1951:Q1 to 2009:Q4. We construct the nominal total market valuation series by using the CRSP data set which includes all stocks listed on the NYSE, the AMEX, and the NASDAQ. We obtain data on nominal output, nominal consumption (of non-durable goods and services), and nominal investment from Bureau of Economic Analysis National Income and Product Accounts (NIPA) Table 1.1.5. We convert each of the above aggregate nominal series into per-capita real series by dividing it by the GDP deflator that is implied by the data on nominal and real GDP (NIPA Tables 1.1.5. and 1.1.6.) and by the civilian noninstitutional population over 16 (BLS LNU00000000Q). We construct the real one-period ahead interest rate series by subtracting the inflation rate implied by the GDP deflator series (constructed as described above) from the nominal yield on the three-month Treasury bill (obtained from the Federal Reserve Board of Governors website). The relative price of investment is obtained by dividing the implicit price deflator for gross private fixed investment (NIPA Table 1.1.9., line 7) by the implicit price deflator for personal consumption expenditures (NIPA Table 1.1.9., line 2). Data on per capita hours is obtained by dividing the Bureau of Labor Statistics' seasonally adjusted non-farm business hours worked index (BLS PRS85006033) by the civilian noninstitutional population over 16 (BLS LNU00000000Q).

Appendix D. Supplementary results

Table D.1
Prior and posterior densities for the SRN model specification.

Parameter	Prior			Posterior		
	Density	Mean	Std	Median	5%	95%
γ	Γ	2.0	2	1.34	1.34	1.35
χ	Γ	3.0	3	1.92	1.91	1.92
θ_I	B	0.50	0.3	0.63	0.62	0.63
θ_c	B	0.50	0.3	0.17	0.17	0.17
δ_2	Γ	0.25	1	0.75	0.75	1.76
η	Γ	0.10	1	1.13	1.12	1.13
ρ_x^s	B	0.50	0.3	0.94	0.94	0.94
ρ_a^s	B	0.50	0.3	0.32	0.32	0.32
ρ_z^s	B	0.50	0.3	0.97	0.97	0.97
ρ_ω^s	B	0.50	0.3	0.96	0.96	0.97
$\sigma_{x,0}$	$I\Gamma$	0.30	2	0.48	0.48	0.48
$\sigma_{x,1}$	$I\Gamma$	0.17	2	0.06	0.06	0.06
$\sigma_{x,2}$	$I\Gamma$	0.17	2	0.05	0.05	0.05
$\sigma_{x,3}$	$I\Gamma$	0.17	2	0.22	0.22	0.22
$\sigma_{a,0}$	$I\Gamma$	0.20	2	0.93	0.92	0.94
$\sigma_{a,1}$	$I\Gamma$	0.12	2	0.10	0.10	0.10
$\sigma_{a,2}$	$I\Gamma$	0.12	2	0.11	0.10	0.11
$\sigma_{a,3}$	$I\Gamma$	0.12	2	0.08	0.08	0.08
$\sigma_{z,0}$	$I\Gamma$	1.00	2	0.78	0.78	0.78
$\sigma_{z,1}$	$I\Gamma$	0.29	2	0.16	0.16	0.16
$\sigma_{z,2}$	$I\Gamma$	0.29	2	0.03	0.03	0.03
$\sigma_{z,3}$	$I\Gamma$	0.29	2	0.09	0.09	0.09
$\sigma_{\omega,0}$	$I\Gamma$	11.9	2	9.95	9.94	9.97
$\sigma_{\omega,1}$	$I\Gamma$	6.87	2	1.12	1.11	1.12
$\sigma_{\omega,2}$	$I\Gamma$	6.87	2	2.34	2.33	2.35
$\sigma_{\omega,3}$	$I\Gamma$	6.87	2	1.04	1.04	1.04
$\sigma_{O,V}$	$I\Gamma$[a]	1.31	1.31	2.62	2.62	2.62
$\sigma_{O,R}$	$I\Gamma$[a]	0.09	0.09	0.10	0.10	0.10

Note: Γ = Gamma distribution, B = Beta distribution, and $I\Gamma$ = Inverted Gamma distribution. The posterior medians and the posterior 5th and 95th percentiles are obtained using the Random Walk Metropolis–Hastings algorithm as described in Appendix B.

[a] Distribution truncated at 30% of the unconditional standard deviation of the corresponding observable variable, as described in Section 3 of the main text.

Table D.2
Prior and posterior densities for the LRN model specification.

Parameter	Prior			Posterior		
	Density	Mean	Std	Median	5%	95%
γ	Γ	2.0	2	0.90	0.89	0.92
χ	Γ	3.0	3	2.90	2.56	3.23
θ_l	B	0.50	0.3	0.12	0.11	0.12
θ_c	B	0.50	0.3	0.22	0.22	0.23
δ_2	Γ	0.25	1	3.91	3.67	4.20
η	Γ	0.10	1	0.29	0.28	0.30
ρ_x^l	B	0.50	0.3	0.01	0.01	0.01
ρ_a^l	B	0.50	0.3	0.32	0.29	0.34
ρ_z^l	B	0.50	0.3	0.57	0.56	0.58
ρ_ω^l	B	0.50	0.3	0.91	0.90	0.91
$\sigma_{x,u}$	$I\Gamma$	0.30	2	1.05	0.99	1.15
$\sigma_{x,LR}$	$I\Gamma$	0.06	2	0.01	0.01	0.01
$\sigma_{a,u}$	$I\Gamma$	0.20	2	0.95	0.89	1.00
$\sigma_{a,LR}$	$I\Gamma$	0.04	2	0.13	0.12	0.14
$\sigma_{z,u}$	$I\Gamma$	1.00	2	0.93	0.90	0.96
$\sigma_{z,LR}$	$I\Gamma$	0.20	2	0.92	0.89	0.95
$\sigma_{\omega,u}$	$I\Gamma$	1.20	2	9.97	9.93	9.99
$\sigma_{\omega,LR}$	$I\Gamma$	0.24	2	0.07	0.06	0.07
$\sigma_{O,V}$	$I\Gamma$[a]	1.31	1.31	2.62	2.62	2.62
$\sigma_{O,R}$	$I\Gamma$[a]	0.09	0.09	0.17	0.17	0.17

Note: Γ = Gamma distribution, B = Beta distribution, and $I\Gamma$ = Inverted Gamma distribution. The posterior medians and the posterior 5th and 95th percentiles are obtained using the Random Walk Metropolis–Hastings algorithm as described in Appendix B.

[a] Distribution truncated at 30% of the unconditional standard deviation of the corresponding observable variable, as described in Section 3 of the main text.

Table D.3
Posterior variance decompositions at business cycle horizons in the SRN model specification *estimation without asset prices in the vector of observables.*

Series\shock	Unanticipated LAT	News LAT	Unanticipated ISP	News ISP	Unanticipated TFP	News TFP	Unanticipated MEI	News MEI
Output growth	0.01	0.00	0.09	0.04	0.44	0.01	0.21	0.20
Consumption growth	0.01	0.01	0.07	0.03	0.56	0.02	0.17	0.13
Investment growth	0.00	0.00	0.03	0.01	0.02	0.00	0.53	0.40
Hours	0.15	0.00	0.10	0.05	0.13	0.00	0.34	0.23
Relative price of investment	0.00	0.00	0.68	0.32	0.00	0.00	0.00	0.00

Note: CAC = capital adjustment costs, SRN = short run news shocks, LAT = labor augmenting technology, ISP = investment-specific productivity, TFP = total factor productivity, MEI = marginal efficiency of investment. Each set of variance decompositions corresponds to medians based on 100 000 draws from the posterior distribution obtained using the Random Walk Metropolis–Hastings algorithm as described in Appendix B. Unlike means, medians need not add up to one. The entries in each of the four (short run) news shock columns represent the sums of the variance decomposition shares attributed to the three anticipated (one, two, and three periods ahead) innovations to the respective shock. Business cycle horizons = 6 to 32 quarters.

Table D.4
Posterior variance decompositions at business cycle horizons in the LRN model specification *estimation without asset prices in the vector of observables.*

Series\shock	Unanticipated LAT	News LAT	Unanticipated ISP	News ISP	Unanticipated TFP	News TFP	Unanticipated MEI	News MEI
Output growth	0.09	0.00	0.09	0.00	0.31	0.00	0.51	0.00
Consumption growth	0.12	0.01	0.07	0.00	0.62	0.00	0.17	0.00
Investment growth	0.01	0.00	0.05	0.00	0.01	0.00	0.92	0.00
Hours	0.15	0.00	0.12	0.01	0.08	0.00	0.63	0.00
Relative price of investment	0.00	0.00	0.99	0.01	0.00	0.00	0.00	0.00

Note: CAC = capital adjustment costs, LRN = long run news shocks, LAT = labor augmenting technology, ISP = investment-specific productivity, TFP = total factor productivity, MEI = marginal efficiency of investment. Each set of variance decompositions corresponds to medians based on 100 000 draws from the posterior distribution obtained using the Random Walk Metropolis–Hastings algorithm as described in Appendix B. Unlike means, medians need not add up to one. Business cycle horizons = 6 to 32 quarters.

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