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Keywords: Anticipated shocks, sources of aggregate fluctuations, Bayesian estimation, DSGE model

JEL classification: C22, E32, E44, G12, G17

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Abstract

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1 Introduction

News shocks, or anticipated shocks to future fundamentals, have been proposed as an important source of business cycle fluctuations.[1] Because asset prices immediately incorporate all the information available to agents, it is natural to extend the scope of the analysis and relate news shocks to the cyclical properties of stock-market returns and valuation ratios. In this paper we estimate a production-based asset pricing model with anticipated shocks using both macroeconomic and financial data, and analyze its implications. We find that information contained in asset prices is key to uncover the importance of anticipated shocks. Conversely, news shocks are important to explain the tendency of the financial variables to "lead" the business cycle.[2]

Our theoretical environment is a real-business-cycle model augmented with Epstein-Zin-Weil preferences, capital adjustment costs, and labor market frictions. This parsimonious setting captures the key trade-offs faced by the agent (intertemporal substitution, time-variation in marginal Tobin's q and labor efficiency wedge) and allows for enough flexibility to match the responses of the economy to exogenous shocks. Our empirical contribution is to analyze the role played by different shocks - anticipated Vs. unanticipated, one-period Vs. multi-period anticipated news, and total factor productivity Vs. investment-specific shocks.

Two main results stand out. First, both for total factor productivity and for investment-specific disturbances, we find a large and significant volatility of four-quarter anticipated shocks, its magnitude being comparable to that of unanticipated innovations. Investment-specific news are an important source of fluctuations in investment and hours. However, investment shocks (contemporaneous or anticipated) account for almost none of the fluctuations in the price-dividend ratio. On the other hand, we find that four-quarter anticipated total factor productivity shocks account for a large fraction (26% and 42% respectively) of the variance of consumption and price-dividend ratio.

Second, and fundamental to our research question, we show that a model with news is able to reproduce the pattern of the lead-lag cross correlations between stock-market returns and valuation ratios and macroeconomic aggregates (output, investment, hours, and consumption), while at the same time it is able to match the unconditional moments of macro- and financial variables. Importantly, in the estimated news model the labor wedge is procyclical. On the contrary, we show

[1]See, e.g. Beaudry and Portier (2006), Barsky and Sims (2011), and Schmitt-Grohé and Uribe (2012).

[2]See Stock and Watson (1989, 2003) and Backus, Routledge, and Zin (2009) for evidence on lead and lag macro-finance correlations in the data.

that when the volatility of news shocks is constrained to be zero, the estimation results imply a countercyclical labor wedge, which is at odds with the data. Taking into account the comovement between macroeconomic quantities and asset prices is instrumental to revealing the importance of news. In fact, when the price-dividend ratio is not included in the estimation, we show that the role of total factor productivity news is greatly downplayed. This is consistent with the first set of results where a variance decomposition of the price-dividend ratio attributes up to 42% of its variability to four-period news. In turn, the model implies that stock-market returns move almost completely contemporaneously with the economic activity, counterfactually with the data.

Identifying news shocks in the data is not trivial. By definition this is information available to agents but not yet reflected in the production possibilities of the economy. In our model representative agent's information set is described by additional latent state variables that keep track of the whole term structure of her expectations about future economic conditions. This proliferation of states makes it less likely that the dynamics of the observables possess a VAR representation, hindering the ability of current and past values of a given set of observables to identify the underlying structural innovations. As a result, in general, a VAR methodology may not identify the anticipated component of structural shocks (see Leeper, Walker, and Yang (2013) for a discussion of the difficulties in extracting information about anticipated shocks via conventional VAR analysis).[3] To address this issue we use a model-based, full-information econometric strategy - as opposed to adopting a VAR approach - to estimate the parameters of the model, in particular the volatilities of news shocks. In doing so we implicitly take advantage of the restrictions imposed by the structural model on the responses of variables to anticipated and un-anticipated shocks. The approach is similar to Schmitt-Grohé and Uribe (2012), but in addition to macroeconomic variables includes stock-market valuations in the estimation.

Our paper is related to Schmitt-Grohé and Uribe (2012), who documented that anticipated shocks are an important source of uncertainty. In this paper we highlighted the different role played by anticipated shocks in investment-specific and technology disturbances for the empirical tendency of valuation ratios and excess returns to lead the business cycle. Our paper is also related to Smets and Wouters (2007) and Justiniano, Primiceri, and Tambalotti (2011), who documented the importance of investment-specific shocks as a source of macroeconomic fluctuations. Differently from

[3]From the econometric point of view this issue is known as the problem of non-fundamentalness, see Rozanov (1967) and Lippi and Reichlin (1994). For a general discussion of the problem of non-fundamentalness, and its implication to evaluate the news view of business cycles, refer to Beaudry and Portier (2014).

Justiniano, Primiceri, and Tambalotti (2011) we show that most of the contribution of investment shocks to volatility of macroeconomic variables is attributable to its anticipated four-period component. Finally our paper relates to a long-standing literature that adopts a VAR approach for the identification of anticipated shocks, see Beaudry and Portier (2006), Barsky and Sims (2011), and Kurmann and Otrok (2013). Differently from these papers we adopt a model-based, full-information estimation strategy. Moreover compared with Kurmann and Otrok (2013) who show that news shocks are closely related to the changes in the slope of the term structure of interest rates, in the present paper we do not consider the pricing of nominal bonds, and focus on stock-market returns and valuation ratios.

The rest of the paper is organized as follows. Section 2 presents our real business-cycle model. Sections 3 presents the estimation methodology. Section 4 presents the estimated parameters, and discusses the contribution of the anticipated and unanticipated components of the disturbances to business-cycle fluctuations. Section 5 present the cross-correlogram of the observable variables in the data and in the baseline model with news. Finally, Section 6 provides a discussion and concludes.

2 Model

2.1 Economy

We consider a setting with several degrees of flexibility that allow it to capture in a parsimonious way the responses of macroeconomic quantities to anticipated total factor and investment specific productivity shocks. First, Epstein-Zin-Weil preferences allow us to separate agent's attitude towards risk aversion and intertemporal substitution.[4] The latter regulates the contemporaneous response of consumption and leisure to anticipated changes in productivity. Second, in addition to elastic labor supply, we introduce a labor efficiency wedge that shifts labor demand. Finally, we also allow for capital adjustment costs.

The representative agent maximizes the utility U_t, recursively defined as

$$U_t = \left(\left[C_t \left(1 - N_t\right)^{\eta} \right]^{1-1/\psi} + \beta \left[E_t \left(U_{t+1}^{1-\gamma} \right) \right]^{\frac{1-1/\psi}{1-\gamma}} \right)^{\frac{1}{1-1/\psi}}, \tag{1}$$

where the period utility $C_t \left(1 - N_t\right)^{\eta}$ depends on her consumption C_t and hours worked N_t. The

[4] See Epstein and Zin (1989), Epstein and Zin (1991), and Weil (1989).

parameter η determines the elasticity of labor supply. Compared to a more standard time-additive utility, this specification of preferences allows us to estimate the elasticity of intertemporal substitution ψ independently from the coefficient of relative risk aversion γ.[5]

The consumption good is produced according to a neoclassical production function $Y_t = (A_t N_t)^{1-\alpha} K_t^{\alpha}$, where Y_t is the output, K_t is the stock of capital, and A_t represents the total factor productivity.[6] The law of motion of capital is given by

$$K_{t+1} = (1-\delta) K_t + \omega_t g\left(\frac{I_t}{K_t}\right) K_t, \tag{2}$$

where I_t is investment. The function $g(\cdot)$ captures the presence of adjustment costs in capital accumulation equal to $\left(\frac{I_t}{K_t} - g\left(\frac{I_t}{K_t}\right)\right) K_t$. Following Jermann (1998) we assume $g\left(\frac{I_t}{K_t}\right) = \zeta_1 \left(\frac{I_t}{K_t}\right)^{\zeta} + \zeta_2$, and at the balanced growth path $g\left(\frac{I}{K}\right) = \frac{I}{K}$ and $g'\left(\frac{I}{K}\right) = 1$. The technology transforming consumption goods into capital goods is subject to a shock ω_t. This type of shock has recently been identified as an important source of aggregate fluctuations by Justiniano, Primiceri, and Tambalotti (2011). As a result of the two assumptions above, the relative price of installed capital in period t available for production in period $t+1$ in terms of consumption goods of period t, or marginal Tobin's q, is equal to $q_t = \frac{1}{\omega_t g'\left(\frac{I_t}{K_t}\right)}$.

The equilibrium in the labour market is determined by the following condition

$$\eta \frac{C_t}{1-N_t} = (1-\alpha) \frac{Y_t}{N_t} h\left(\tilde{Y}_t\right). \tag{3}$$

The left-hand side of (3) is the marginal rate of substitution between consumption and labor implied by agent's preferences $-\frac{\partial C_t (1-N_t)^{\eta}}{\partial N_t} / \frac{\partial C_t (1-N_t)^{\eta}}{\partial C_t}$. The right-hand side is the marginal product of labor $\frac{\partial Y_t}{\partial N_t}$ multiplied by the labor efficiency wedge $h\left(\tilde{Y}_t\right)$. In absence of labor market frictions the wedge term is equal to 1. We build on Chari, Kehoe, and McGrattan (2007) who show that models with labor market frictions, such as wage rigidity in a monetary economy, can be mapped into a (real) model with a wedge. From a technical point of view the wedge can be seen as a tax that distorts agent's first order conditions in a way equivalent to the friction. Importantly the observed wedge

[5] Swanson (2012) proposes several definitions of risk aversion in the context of flexible labor margin that are either equal to γ or increasing in it.

[6] Given our interest in the role of news shocks for the understanding of the comovements between macroeconomic quantities and asset prices, it is key to have labor in the production function. In fact, labor tends to lag the cycle, which would mean that some movements in a_t would be predictable. A model with no labor in the production function could, erroneously, interpret this as news. We thank Simon Gilchrist for raising this point to our attention.

$\frac{C_t}{1-N_t}\frac{N_t}{Y_t}$ is highly procyclical as it is displayed in Figure 1.[7]

[Insert Figure 1 about here]

Hall (2011) and Gourio (2012) point to countercyclical markups as a potential explanation. We do not model the sources of the cyclical variation. Instead, following these authors, we postulate a reduced form for $h(\cdot)$ as a function of (detrended) output $\tilde{Y}_t$ that would allow the model to match the stylized fact. We assume $\frac{h'(\tilde{Y}_t)\tilde{Y}_t}{h(\tilde{Y}_t)} = \lambda$ and at the balanced growth path $h\left(\tilde{Y}\right) = 1$.

Denote the total factor productivity growth and investment shocks as:

$$\Delta \ln A_t = x_{1,t} \ ,$$

$$\ln \omega_t = x_{2,t} \ .$$

We specify $x_{i,t}$, $i = 1, 2$, as autoregressive and subject to anticipated and unanticipated innovations[8]

$$x_{i,t} = (1-\rho_i)\mu_i + \rho_i x_{i,t-1} + \sum_{j=0}^{H} \varepsilon_{i,t-j}^{j}. \tag{4}$$

$\varepsilon_{i,t}^0$ are date t productivity surprises. Innovations $\varepsilon_{i,t-j}^j$ are anticipated j periods ahead: they affect date-t productivity, but are period $t-j$ information. In other words, at date t the agent learns about $2 \times (H+1)$ innovations that affect productivity immediately ($\varepsilon_{i,t}^0$) and in up to H periods ahead ($\varepsilon_{i,t}^H$). We assume all innovations to be independent and normally distributed. The shock structure can be easily written as a first order vector autoregressive system

$$x_{t+1} = H_0 + H_1 x_t + H_2 \epsilon_{t+1},$$

with $x_{1,t}$ and $x_{2,t}$ being the first two elements of the vector x_t, $\epsilon_t \sim N(0, I_{6\times 6})$ and H_0, H_1, H_2 conforming matrices (see Appendix A).

[7] This empirical evidence has been highlighted by U. Jerman in a discussion at the NBER Summer Institute AP 2010.

[8] We borrow this specification from Schmitt-Grohé and Uribe (2012).

In addition to equations (2) and (3), and (4) equilibrium is characterized by

$$E_t\left(M_{t+1}\frac{\alpha\left(\frac{A_tN_t}{K_t}\right)^{1-\alpha}+q_{t+1}\left(1-\delta+\omega_{t+1}\left(1-\zeta\right)g\left(\frac{I_{t+1}}{K_{t+1}}\right)\right)}{q_t}\right)=1,$$

$$V_t^{1-1/\psi}=\left[C_t\left(1-N_t\right)^{\eta}\right]^{1-1/\psi}+\beta\left[E_t\left(V_{t+1}^{1-\gamma}\right)\right]^{\frac{1-1/\psi}{1-\gamma}},$$

$$C_t+I_t=\left(\alpha+\left(1-\alpha\right)h\left(\tilde{Y}_t\right)\right)Y_t,$$

where V_t is agent's value function and $M_{t+1}=\frac{\partial V_t/\partial C_{t+1}}{\partial V_t/\partial C_t}$ is the stochastic discount factor

$$M_{t+1}=\beta\left(\frac{V_{t+1}}{E_t\left(V_{t+1}^{1-\gamma}\right)^{\frac{1}{1-\gamma}}}\right)^{1/\psi-\gamma}\left(\frac{C_{t+1}}{C_t}\right)^{-1/\psi}. \tag{5}$$

2.2 Stock Prices

In equilibrium the return on any asset k, $R_{k,t+1}$, satisfies

$$E_t\left(M_{t+1}R_{k,t+1}\right)=1. \tag{6}$$

From (5), provided the agent is not indifferent towards the timing of the resolution of uncertainty ($1/\psi\neq\gamma$) innovations to expected consumption growth enters the stochastic discount factor alongside realized consumption growth through the V_{t+1} term. Thus, both innovations to realized and expected consumption growth are priced risk factors. This key feature implies that news about future consumption will matter for the level of risk premia. We follow a standard approach in finance literature and take the leveraged consumption claim as the model counterpart of the stock-market.[9] We assume that fluctuations in aggregate dividend growth around trend total factor productivity growth are equal to the fluctuations in consumption growth around the same trend amplified by the leverage parameter ϕ:

$$\frac{D_{t+1}}{D_t}=\left(\frac{C_{t+1}}{C_t}\right)^{\phi}e^{(1-\phi)\mu}.$$

[9] This is an assumption common in asset pricing literature. It can be motivated by the fact that in the data aggregate dividend growth and aggregate consumption growth are correlated, but dividend growth is significantly more volatile. See for example Bansal and Yaron (2004). Also, Lustig, van Nieuwerburgh, and Verdelhan (2012) find that both risk premia and volatility are lower for the consumption claim compared to the stock-market.

In particular, when $\phi = 1$, the asset is simply the claim on aggregate consumption stream, or total wealth. $\phi > 1$ is a reduced-form way to model both operational and financial leverage. Substituting the total return - the sum of dividend and capital gain - on the dividend claims in the asset pricing equation (6) provides us with a recursive definition of the price to dividend ratio PD_t, that can be easily solved for using perturbation methods:

$$PD_t = E_t \left(M_{t+1} \frac{D_{t+1} \left(PD_{t+1} + 1 \right)}{D_t} \right).$$

3 Bayesian inference and the observable variables

We use Bayesian methods to characterize the posterior distribution of the structural parameters of the model (see An and Schorfheide (2007) for a survey). Since the exogenous forcing process A_t display a stochastic trend and this trend is inherited by the endogenous variables of the model, before estimating the model we perform a stationarity-inducing transformation. In particular, we divide the endogenous variables by their productivity trend component to focus our attention on equilibrium fluctuations around these stochastic trends (see Appendix B).

We then compute a log-linear approximation to the equilibrium dynamics of the model.[10] In Appendix C we show how to express the law of motion of the exogenous driving forces a_t and ω_t of the model in a first-order autoregressive form. Using familiar perturbation techniques (e.g., Schmitt-Grohe and Uribe, 2004), one can write the equilibrium dynamics of the model up to first order as

$$\begin{aligned} x_{t+1} &= h_x x_t + \xi_v \nu_{t+1} \\ y_t &= g_x x_t + \xi_e e_{t+1} \end{aligned} \tag{7}$$

where x_t is a vector of endogenous and exogenous state variables, y_t is the vector of observables, ν_{t+1} is a vector of structural disturbances distributed N(0, I), and e_{t+1} is a vector of measurement errors distributed N(0, I). The matrices h_x, g_x, and ξ_v are functions of the structural parameters

[10] We use perturbation methods to solve the model and implement likelihood-based inference. Our specification of news contains a large number of state variables that keep track of the whole term structure of representative agent's expectations. Methods such as value function iteration are inadequate because of the dimensionality problem. Our approach draws on Schmitt-Grohe and Uribe (2004) methodology for approximating a general class of dynamic stochastic general equilibrium models up to the second order.

of the model. Given the system of equations in (7) describing the equilibrium dynamics of the model up to first order, it is straightforward to numerically evaluate the likelihood function of the data given the vector of estimated parameters. The posterior distribution combines the likelihood function with prior information. The rest of this section discusses the data used to evaluate the likelihood function and the specification of the priors.

3.1 Data

We estimate the model on U.S. quarterly data ranging from 1948:QII to 2013:QIV. The data include five time series: the growth rates of real GDP, real consumption, real investment, the level of hours and the price-dividend ratio. Formally, the vector of observable variables y_t is given by

$$[\Delta \log Y_t,\ \Delta \log C_t, \log H_t, \Delta \log I_t, \log PD_t]$$

where Δ denotes the temporal difference operator. The inclusion of financial variables in the econometric estimation of our model is motivated by the empirical literature on anticipated shocks which documents that stock prices are informative about anticipated changes in fundamentals (see, for instance, Beaudry and Portier (2006)). With regard to the financial variable, we consider an adjusted price-divided ratio, which accounts for potential shifts in its long-run mean (see Lettau and Nieuwerburgh (2008) and Favero, Gozluklu, and Tamoni (2011)). The reason is twofold: first, the adjusted price-divided ratio allows us to focus on the cyclical fluctuations in the series which we are aiming at explaining in this paper (rather than low frequency changes). Secondly and more importantly, the lead-lag pattern between valuation ratios and macroeconomic quantities, which is the central focus of our analysis, can be entirely attributed to the cyclical component in price-dividend. On this ground our use of an adjusted price-dividend ratio seems justified. Figure 2 display the log price-dividend ratio along with its business cycle component used in the estimation procedure, as well as its long-term trend.[11]

[Insert Figure 2 about here]

[11] To separate the log price-dividend ratio into the business-cycle and trend components, we employ the persistence-based decomposition suggested in Ortu, Tamoni, and Tebaldi (2013). Importantly, the business cycle component extracted using this decomposition is adapted to time t information and is, therefore, non anticipative. Our results do not hinge on the filtering approach, however. We obtain very similar parameter estimates if we use a one-sided Hodrick-Prescott decomposition of the price-dividend ratio, or a break-adjusted price-dividend series (as suggested in Lettau et al. 2008) or, again, a price-dividend ratio adjusted for demographic trends (as in Favero et al. 2011).

The figure highlights the persistent increase in the long-term component of the price-dividend ratio. This trend component has been attributed to persistent changes in the tax code (see McGrattan and Prescott 2005), to changes in stock market participation (see Vissing-Jorgensen (2002)), or to long-run demographic trends (see Favero, Gozluklu, and Tamoni (2011)). In this paper we do not take a stand on what causes the trend behavior in the log price-dividend ratio, and we just simply focus our analysis on the adjusted (ie. detrended) valuation ratio. Finally, we assume that output growth is measured with error.[12] We set the standard deviation of the measurement error as 20% of that of the observation. Appendix D provides more detailed information about the data used in the estimation of the model.

3.2 Structural and News Shocks

Our model of the business cycle is driven by two exogenous disturbances: technology a_t and investment–specific ω_t. We assume that all of these forces are subject to anticipated as well as unanticipated innovations. The maximum news horizon H is assumed equal to four quarters in our baseline estimation and we study a formulation with one- and four-quarter anticipated shocks.[13] Our horizon structure is, therefore, denser than the one in Schmitt-Grohé and Uribe (2012), who impose news at horizons 4 and 8 only, but with the drawback that we do not include longer-term news.

3.3 Priors

We fix a small number of parameters to values commonly used in the literature (see, e.g. Christiano, Boldrin, and Fisher (2001), and references therein). In particular, we set the time discount parameter (β) to 0.998, the quarterly depreciation rate of capital (δ) to 0.025, the capital share (α) is 0.34, and the quarterly log technology growth rate (μ) is 0.4%.

Table 1 summarizes the priors for the remaining parameters of the model. These priors are relatively disperse and broadly in line with those adopted in previous studies (see Schmitt-Grohe and Uribe, 2012).

[12] Allowing for measurement error in output is required by the fact that, up to first order, the resource constraint of the model economy postulates a linear restriction among the observed observables. The interest reader is referred to An and Schorfheide (2007) for the role of measurement errors in the analysis of DSGE models.

[13] In a previous version of this paper we also experiment with two, and three quarters anticipated components. Results suggest that this denser anticipation structure does not lead to any significant improvement in terms of model's fit.

[Insert Table 1 about here]

Of particular importance among the priors are those associated with the parameters of the stochastic processes of anticipated and unanticipated innovations. In particular, for the standard deviations of unanticipated and news shocks we follow Schmitt-Grohé and Uribe (2012) in assuming that these standard deviations obey a Gamma prior distribution. Gamma priors with equal values for the mean and standard deviations ensure that values close to 0 are assigned higher probability than positive and larger values and that 0 is also a value with positive probability mass. Given that the model has more shocks than observables, this choice ensures that the data pick the most influential shocks, rather than spuriously forcing each shock to have a positive standard deviation. As in Schmitt-Grohé and Uribe (2012), the unanticipated shocks are assumed to account for 75% of the a priori variance, while the two news shocks for each disturbance account for the remaining 25%; therefore, for each disturbance j, we select the prior mean so that $\frac{\left(\sigma_x^{(0)}\right)^2}{\left(\sigma_x^{(0)}\right)^2+\left(\sigma_x^{(1)}\right)^2+\left(\sigma_x^{(4)}\right)^2} = 0.75$, where $x = a, \omega$. The priors, therefore, make sure that news shocks are not unduly favored. For persistence parameters we use a Beta prior. In particular, for the autocorrelation of neutral ($\Delta \ln A_t$) and investment-specific ($\ln \omega_t$) technology shocks we center the prior at 0.4 and 0.6 respectively. With regard to the labor wedge, we do not a priori constrain the parameter λ to take a positive value (procyclical labor wedge) and, instead, we assume a Normal prior centered around $\lambda = 0$ (no distortion to agent's first order conditions). Finally we use an uninformative uniform prior for the elasticity if labor supply η, investment adjustment costs ζ and leverage ϕ parameters. We have also experimented with more informative normal priors for these parameters and, given that the data appear very informative, the results were similar.

4 Estimation results

This section presents our main results in terms of parameter estimates, impulse responses, cross-correlogram of the observable variables in the news model and the data and variance decomposition.

4.1 Estimated Parameters

The last column of Table 1 reports the posterior estimates of the model's parameters.[14] Our estimates for the preference, technology, and market friction parameters are in line with the previous literature. Our estimate for the elasticity of intertemporal elasticity of substitution (IES) $\psi = 1.95$ is greater than one, in line with the values used in the long-run risk literature, see for instance Bansal and Yaron (2004), Kaltenbrunner and Lochstoer (2010) and Croce (2014). The high value for the IES implies a weak wealth effect. Anticipating on the discussion below, when elasticity is high agents respond to expected productivity improvements by only a small immediate increase in consumption, whereas when wealth effects are strong, agents immediately "consume away" anticipated increases in productivity. In the latter case, we would observe a low or negative correlation between asset valuation and subsequent growth in output, consumption, and investment. Our estimate of the parameter $\zeta = 0.79$ implies moderate capital adjustment costs, in line with e.g. Kaltenbrunner and Lochstoer (2010). The parameter $\phi = 4.89$ measures both operational and financial leverage, its value is in line with Bansal and Yaron (2004) who uses the values of three and five. Note that at the same time the value for the risk aversion parameter $\gamma = 3.06$ is very conservative.[15] Finally, the positive value for the labor efficient wedge parameter $\lambda = 1.45$ implies that the wedge is procyclical, in line with Hall (2011) and the evidence in Figure 1.

[Insert Table 1 about here]

4.2 News Shocks

Given our focus on the importance for news in DSGE models, we pay particular attention to the estimated parameters for the anticipated and unanticipated innovations. From an economic point

[14] To gauge the ability of our empirical strategy to identify the parameter vector Θ, we perform two identification tests. First, we check for the identifiability of the estimated parameter vector Θ by applying the test proposed by Iskrev (2010). See Schmitt-Grohe and Uribe (2011b) section 3 for details on the implementation of this test. Full column rank obtains starting with the inclusion of covariances of order 0 and 1. According to this test, therefore, the parameter vector Θ is identifiable in the neighborhood of our estimate. Our second identification test consists in applying our estimation strategy to artificial data stemming from the RBC model to show that our proposed empirical approach can recover the underlying parameters. The results show that, given the size of the artificial data sample, the likelihood-based estimation procedure capture the true parameter values reasonably well.

[15] The parameters γ and ϕ affect the level and volatility of the price-dividend ratio. For instance, it can be shown that leverage increases the volatility of price-dividend ratio and stock-market returns by a factor $\frac{\phi-1/\psi}{1-1/\psi}$. The coefficient of relative risk aversion γ does not appear in the log-linearized dynamics of the variables. Therefore, the only moment that has to be adjusted for risk and agent's attitude towards risk is the unconditional mean of the price-dividend ratio. We use the second order approximation of the model and choose γ to match this moment.

of view, our results speak about how many quarters in advance are the main drivers of business cycles anticipated. Our estimation assigns a prominent role to the four-quarter-anticipated news ($\epsilon^4_{x,t},\ x = a, \omega$) about future changes in total factor and investment goods sector productivity, their volatility being comparable to the unanticipated one. Overall our estimation allows us to distinguish changes in fundamentals by their anticipation horizon, and suggest that farther in the future anticipated news play a key role to explain fluctuations in macroeconomic and financial series.

To further understand the importance of anticipated shocks as a source of fluctuations in macroeconomic quantities and asset prices, we present the variance decomposition for our model. Table 2-Panel A reports the contribution of the shocks – contemporaneous and anticipated – to the unconditional variances of model-implied macroeconomic and financial variables. Table 2-Panel B performs a similar exercise, the only difference being that the contribution refers to the variance at business cycle frequencies.

[**Insert Table 2 about here**]

Two results stand out. First, when we look at the financial variable in our system, Table 2 shows that four-quarter anticipated productivity shocks account for 42 percent of the variance of price-dividend ratio. On the contrary, we find that investment shocks – contemporaneous or anticipated – account for almost 0 percent of the fluctuations in the price-dividend ratio. Secondly, Table 2 shows that (marginal efficiency of) investment shocks are responsible for 45, 56 and 56 percent of the variance of GDP, hours and investment respectively, although they explain little of consumption variability. This result is in line, e.g., with Justiniano et al. (2011). What is new is that most of the contribution of investment shocks to volatility of macroeconomic variables is attributable to its anticipated four-period component.

Panel B of table Table 2 shows that the role of anticipated shocks is also estimated to be prominent when one measures the business-cycle component of a time series. Overall, anticipated shocks explain between 50 and 81 percent of the variances of the four macroeconomic indicators considered, and 53 percent of the price-dividend ratio. These results suggest that the importance of anticipated shocks in accounting for variations in business fluctuations is robust to detrending the predicted time series using growth rates or using business-cycle filtered components.

5 Model Fit

Given our posterior estimates, how well does the model fit the data? We address this question by comparing a set of statistics implied by the model to those measured in the data with a particular focus on the comovements between macroeconomic quantities and asset prices.

5.1 Cross-Correlations

First, we look at the cross-correlation function between financial and macroeconomic variables. Among the financial variables we consider the price-dividend ratio (used in our estimation) and, for comparability with previous studies, the stock market returns.[16] Figure 3 displays the cross-correlogram for the data (line with cross) and the model (line with circle), along with the 90 percent posterior intervals for the model implied by parameter and small-sample uncertainty.

[Insert Figure 3 about here]

Note that for negative values of k, the figure displays the correlation of the financial indicator with future economic growth. If these correlations are nonzero, we say the financial indicator leads the business cycle. Similarly, positive values of k correspond to correlations of the indicator with past economic growth; nonzero values suggest a lagging indicator. Figure 3 shows the well-known tendency for equity prices (or their growth rates) to lead the business cycle: In US data, fluctuations in excess returns (Panel A) and the price-dividend ratio (Panel B) are positively correlated with economic growth, as measured by either output, consumption, investment or hours worked, up to 12 months in the future (for further evidence on the cyclical behavior between financial variables and economic growth, see King and Watson (1996) and Backus, Routledge, and Zin (2009), among others). The model is quite successful in mimicking the observed cyclical behavior of excess returns and economic growth: high excess returns (Panel A) and price-dividend (Panel B) are associated with high future growth.[17, 18]

[16] Returns are obtained from the price-dividend ratio, PD_t, and dividends, D_t, as: $R_{t+1} = \frac{D_{t+1}}{D_t} \frac{PD_{t+1}+1}{PD_t}$.

[17] To focus on business cycles, we follow Backus, Routledge, and Zin (2009) and we use centered year-on-year growth rates, and average annual returns. We think of year-on-year growth rates and returns as crude approximations to the Hodrick-Prescott filter often used in business cycle analysis. Importantly the exact same transformation is applied to the data and the model implied variables.

[18] We mainly look at cross-correlation function for the excess return on equity and the growth rate of macroeconomic quantities. In the data, the correlations for excess returns are slightly larger than those for returns, but the pattern is similar. In other words, most of the variation in excess returns comes from the return rather than the short rate.

To what extent the lead and lag correlations between financial and macroeconomic variables are important to uncover the importance of anticipated shocks? To answer this question we repeat the estimation exercise but, this time, we exclude the price-dividend ratio from the vector of observable variables.[19] We find that preferences and technology parameters remain in line with our baseline estimates. In particular, the estimated labor wedge parameter $\lambda = 1.996$ implies a procyclical wedge. The volatility of four-period anticipated shocks in investment is similar in magnitude to the estimate reported in Table 1. The main difference when the price-dividend ratio is not included in the estimation is that the posterior distribution assigns only a limited role to the four- and one-quarter-anticipated news about total factor productivity. The posterior mode of four- and one-period volatility (0.012% and 0.038% respectively) is considerably lower to that of the unanticipated productivity shock (0.197%). This is consistent with the results in Table 2 which show that 42% of the price-dividend variability can be attributed to four-period productivity news. Importantly, Figure 4 shows that this model where news in productivity are effectively absent, implies that return moves (almost) completely contemporaneously with the economic activity, a fact at odds with the data. In all, the price-dividend ratio is key to identify (the volatility of) anticipated shocks about productivity, and, in turn, these productivity news are essential for the model to reproduce the empirical tendency for stock-market valuations and excess returns to lead the business cycle.

[Insert Figure 4 about here]

Can a model without news match the lead of stock-market returns and valuation ratios over the business cycle? To answer this question we repeat the estimation exercise but constrain the volatility of anticipated shocks to be 0. The results exhibit an important difference compared to our baseline estimates: the negative labor wedge parameter $\lambda = -0.563$ implies a countercyclical wedge, contrary to what is observed in the data. This happens because, in absence of news shocks, the estimated model is trying to match macro-finance comovements (see Figure 5) through a negative response of hours to total factor productivity surprises. When productivity and output increase, the labor demand curve shifts down. This slows growth down and leads to a delayed response of macroeconomic aggregates. Because this alternative mechanism is inconsistent with the procyclical behavior of hours and labor efficiency wedge, it is eliminated in the estimation process when we allow for news shocks.

[19]The full set of estimates is not shown here but is available upon request.

[Insert Figure 5 about here]

5.2 Other moments

Table 3 reports the model's predictions regarding standard deviations (in absolute terms as well as relative to that of output growth), correlations with output growth, and serial correlations of the five time series included as observables in the estimation. For each moment, we report the median and the 90 percent probability intervals that account for both parameter and small-sample uncertainty. For comparison, the table also shows the corresponding empirical second moments calculated over the sample 1948:QII to 2013:QIV.

The model matches fairly well the volatility of output, hours and price-dividend ratio, the first order autocorrelation of consumption and price-dividend ratio, as well as the standard deviation of consumption relative to output growth. The model also captures well the contemporaneous correlations with output growth of consumption and hours. The most notable discrepancies between model predictions and data can be found in the too high volatility of investment.

[Insert Table 3 about here]

It is important to note that our likelihood-based estimator tries to match the entire autocovariance function of the data, and thus must strike a balance between matching standard deviations, first order autocorrelations and all the other second moments (e.g. the cross-correlogramm of stock-market valuations and macroeconomic growth rates, see again Figure 3).

To provide another perspective on the comparability of the posterior estimates in Table 1 with those in the literature, Fig. 6–10 displays the impulse responses to anticipated and unanticipated innovations. The median responses are solid black and the shaded gray areas are the 90% confidence bands calculated using draws from the posterior distribution. Following a positive four-period productivity news shock, output, hours, and investment all decline on impact in the model. Only after TFP begins to increase do these series begin to rise. These responses become large over time, and comparable in magnitude to the surprise technology shock. The on-impact response of consumption to the four-quarter anticipated innovation in technology is instead not significantly different from zero. These responses are at broadly consistent with the implications of conventional neoclassical models: there is no large output “boom” in anticipation of increases in TFP. Moreover our model responses largely agree with the empirical responses identified in Barsky and Sims (2011) using a VAR in four variables - the levels of utilization adjusted TFP series, real consumption, real output and hours per-capita.[20]

Fig. 10 shows the responses of stock prices to a productivity shock – anticipated and unanticipated. Following a positive four-period productivity news shock, stock prices rises significantly on impact, with only some evidence of mild reversion at longer horizons. This implication of the model is consistent with the empirical results in Beaudry and Portier (2006).

[**Insert Figure 6–10 about here**]

Turning to the investment-specific shocks (right panels), we observe a large negative effects of four-quarter anticipated innovation on output and hours: a 1% shock in four-quarter anticipated investment shocks, produce a 4.74% and 6.84% decrease in output and hours, respectively.[21]

6 Conclusion

In this paper we assess the role of anticipated shocks through the lens of a structural model estimated using both macroeconomic and financial data. We find that the comovements between macroeconomic and financial series, in particular the tendency of stock-market valuations and returns to lead the business cycle, are key to uncover the importance of total factor productivity news.

Whereas this paper mainly focuses on the comovement between asset prices and the macroeconomy, our results speak also to the consumption-based asset pricing literature. For instance, our variance decomposition shows that news shocks explain a large fraction of consumption and price-dividend ratio variability. This result hints at a potential role for news to help understanding expected returns. The pricing of news shocks, their contribution to the explanation of the equity risk premium and to the cross-section of asset returns is a promising avenue of future research.

[20]Consistent with the small value estimated for the volatility of one-period productivity news - see Table 1 -, the responses to the one-quarter anticipated innovation in technology are not significantly different from zero for hours and investment, and only marginally so, yet small in terms of economic magnitude, for output and consumption. The estimated responses to the surprise technology shock are standard.

[21]To get these numbers, observe that the median estimate for the standard deviation of a four-quarter investment shocks is equal to .19 (see Table 1), and that the four-period median IRF is equal to -0.9 and -1.3 for output and hours, respectively. This yields $-.9/.19 = -4.74\%$ and $-1.3/.19 = 6.84\%$.

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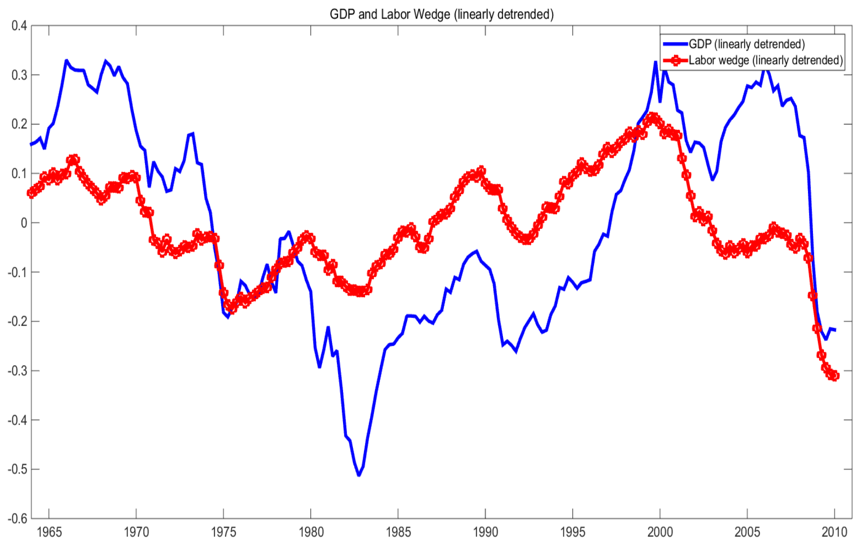


Figure 1: Labor efficiency wedge: The figure displays GDP (solid line) and the observed labor wedge $\frac{c_t}{1-n_t}\frac{n_t}{y_t}$ (solid line with circles). Both series have been linearly detrended.

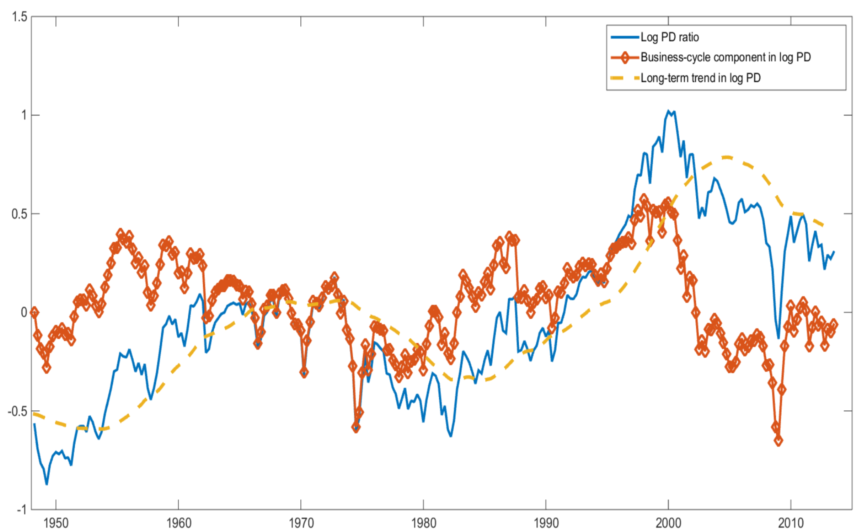
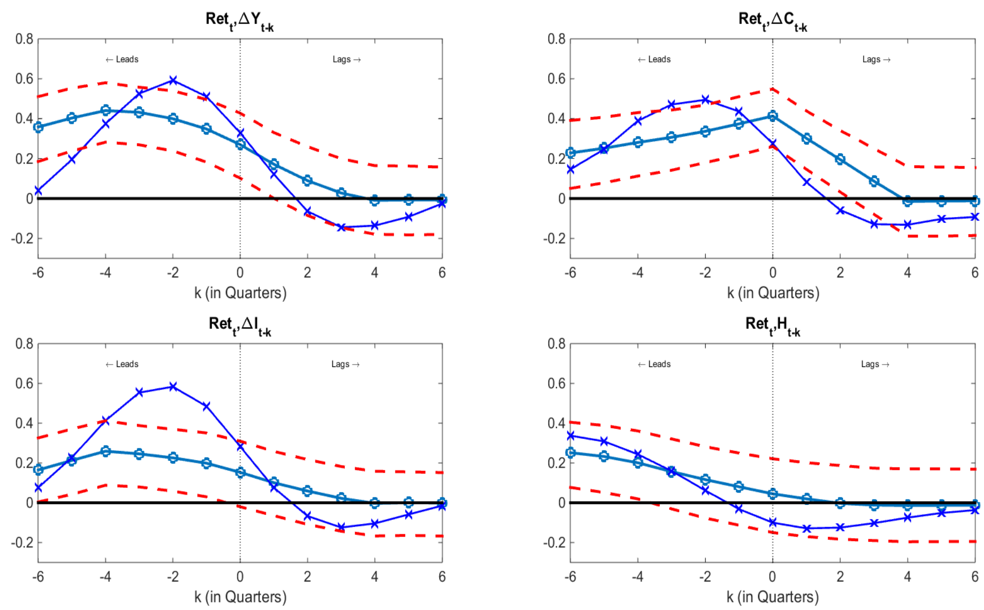
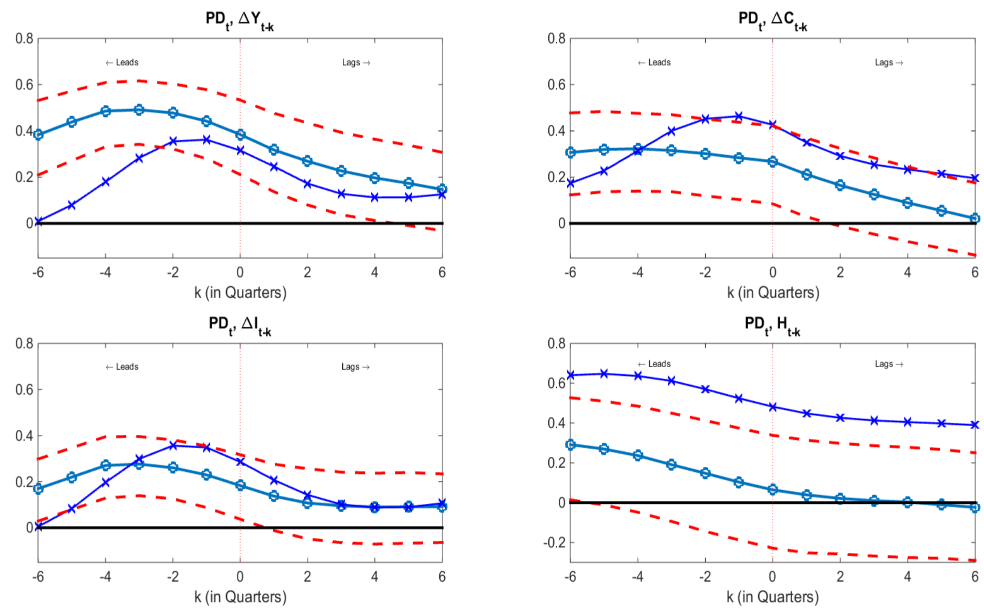


Figure 2: PD ratio: The figure displays the log price-dividend ratio (solid line), and its decomposition into a business cycle component (solid line with diamonds), and a long-term trend (dashed line). All series are demeaned.



(a) Cross-correlogram with market returns



(b) Cross-correlogram with price-dividend ratio

Figure 3: **News Model.** Cross-correlogram of the macro-observable variables and the financial variables in the news model and the data. The blue line with cross is the data. The solid cyan line with circle is the model's median and the dashed lines are the model's 5th and 95th percentiles.

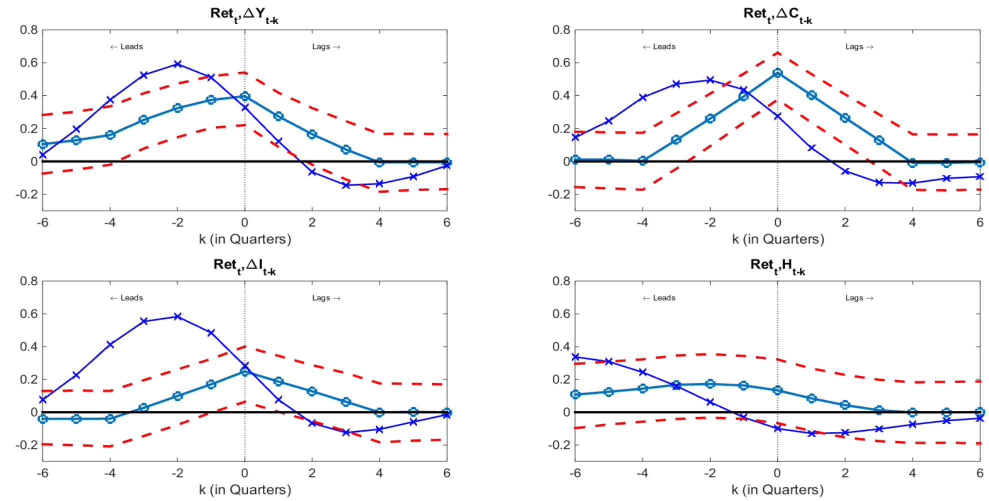


Figure 4: **News Model estimated without using price-dividend ratio.** Cross-correlogram of the macro-observable variables and the financial variables in the news model and the data when the price-dividend ratio is not used in the estimation. The blue line with cross is the data. The solid cyan line with circle is the model's median and the dashed lines are the model's 5th and 95th percentiles.

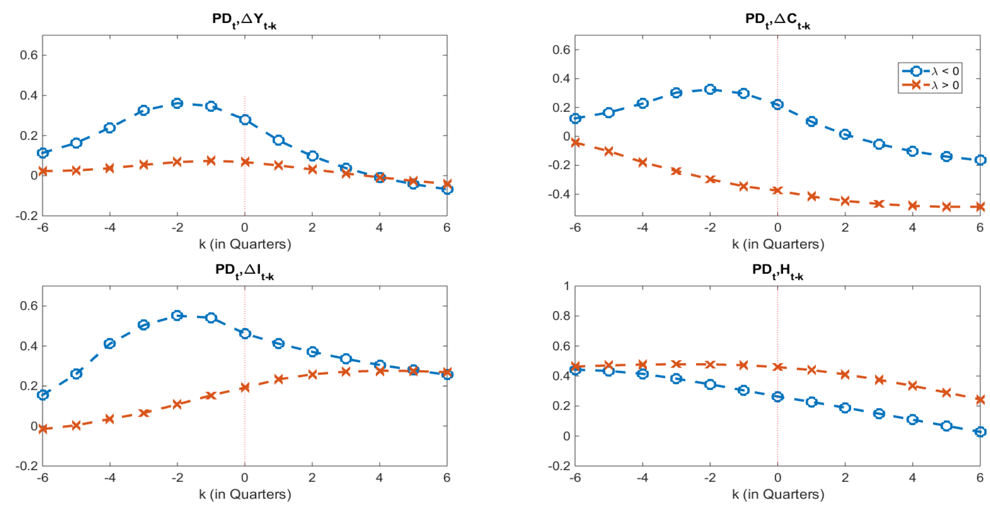


Figure 5: **Model without anticipated disturbances.** Cross-correlogram of the macro-observable variables and the financial variables in the model with no news and the data (the price-dividend ratio is still used in the estimation). The blue line with cross is the data. The solid cyan line with circle is the model's median and the dashed lines are the model's 5th and 95th percentiles.

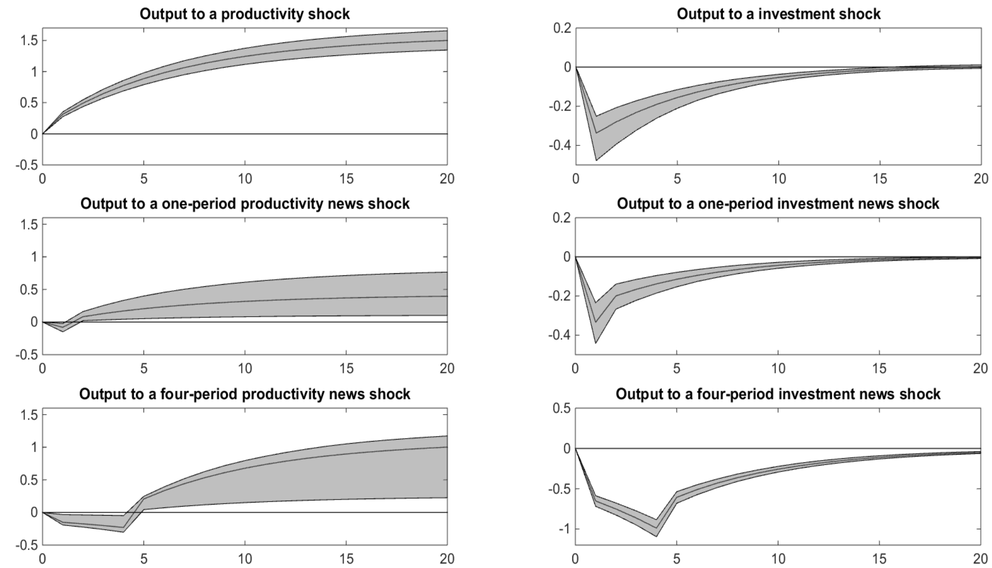


Figure 6: Impulse responses of output to a one standard deviation shock. The solid line is the median, while the dotted lines are the 5th and 95th percentiles. The horizontal axes refer to forecast horizons (in quarters) and the units of the vertical axes are percentage deviations.

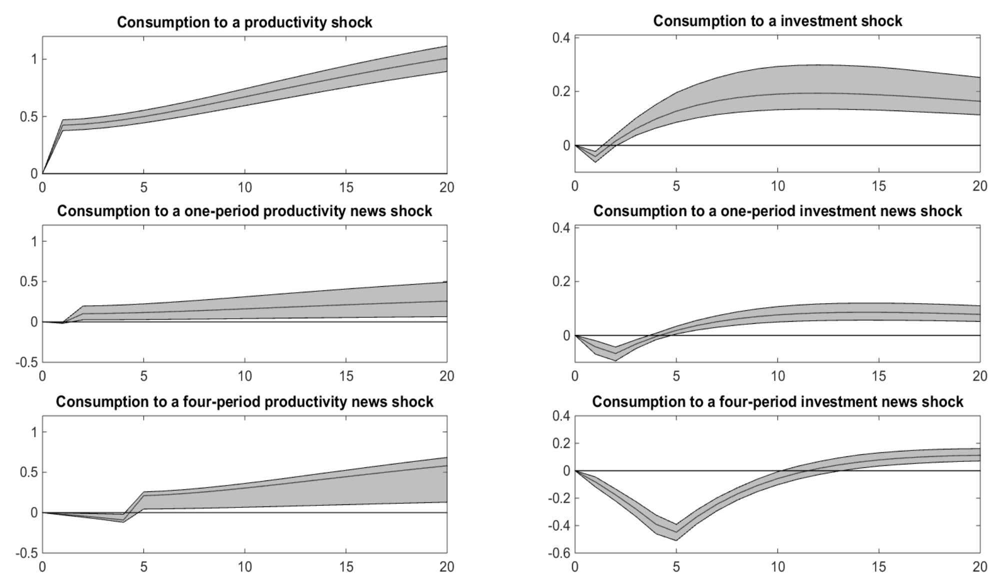


Figure 7: Impulse responses of consumption to a one standard deviation shock. The solid line is the median, while the dotted lines are the 5th and 95th percentiles. The horizontal axes refer to forecast horizons (in quarters) and the units of the vertical axes are percentage deviations.

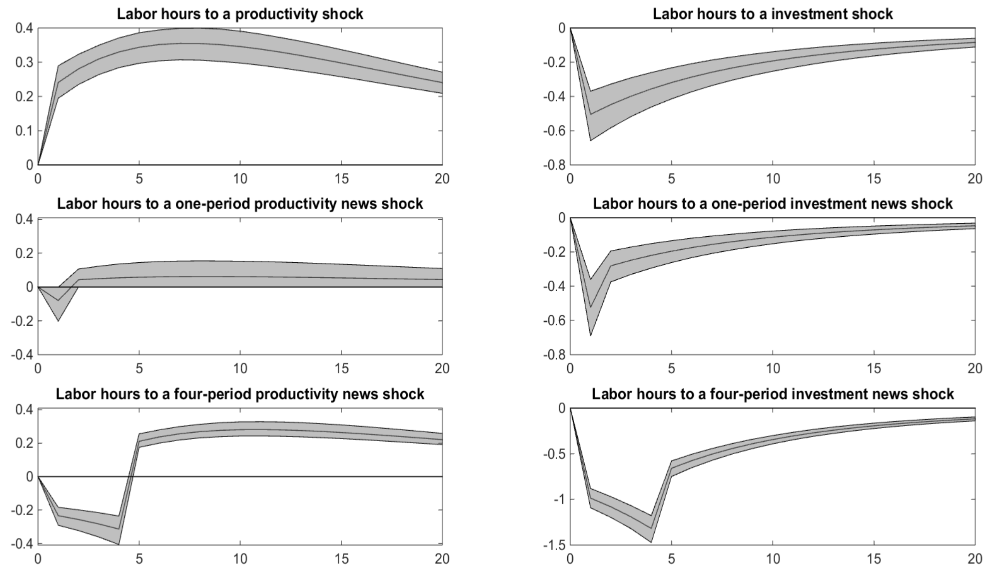


Figure 8: Impulse responses of hours to a one standard deviation shock. The solid line is the median, while the dotted lines are the 5th and 95th percentiles. The horizontal axes refer to forecast horizons (in quarters) and the units of the vertical axes are percentage deviations.

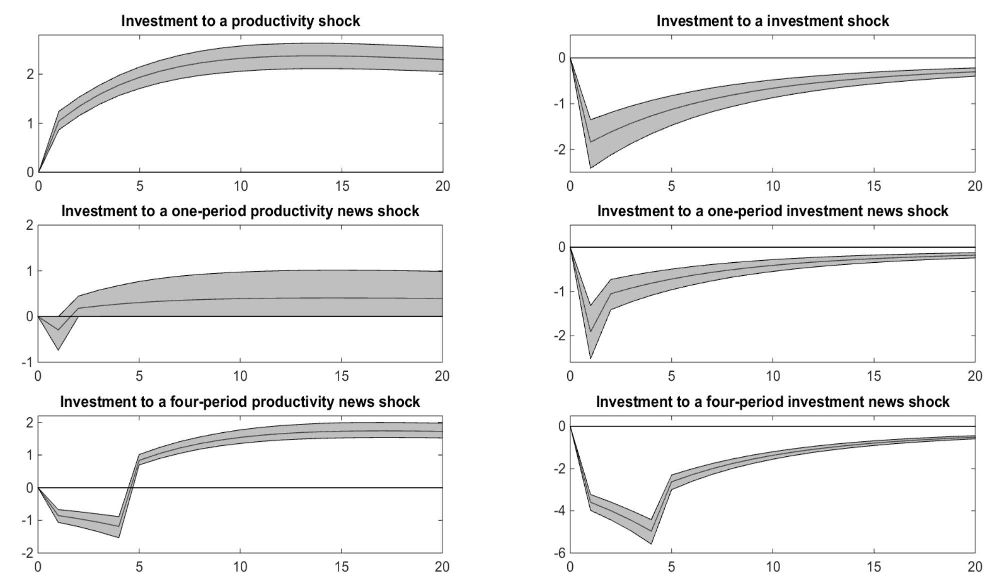


Figure 9: Impulse responses of investment to a one standard deviation shock. The solid line is the median, while the dotted lines are the 5th and 95th percentiles. The horizontal axes refer to forecast horizons (in quarters) and the units of the vertical axes are percentage deviations.

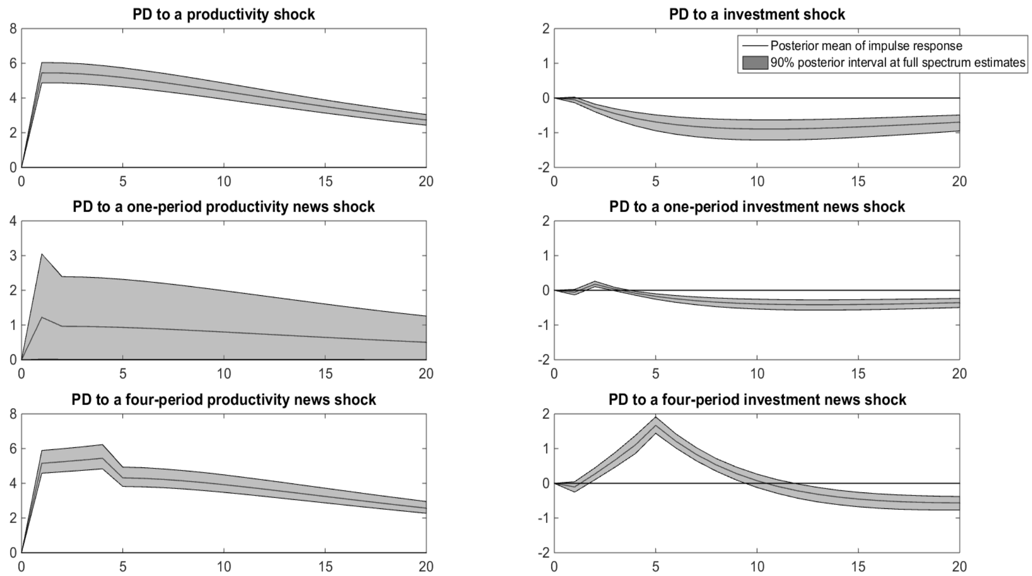


Figure 10: Impulse responses of price-dividend to a one standard deviation shock. The solid line is the median, while the dotted lines are the 5th and 95th percentiles. The horizontal axes refer to forecast horizons (in quarters) and the units of the vertical axes are percentage deviations.

Coefficient	Description	Prior			Posterior				
		Density	Mean	Std	Mode	Median	Std	[5th,	95th]
ψ	Intertemporal Elasticity	N	1.0	0.5	1.95	1.94	0.05	[1.82,	1.99]
η	Elasticity of Labor supply	U	1.05	0.55	1.80	1.86	0.08	[1.69,	1.94]
ξ	Investment adjustment costs	U	-1.50	1.44	0.79	0.80	0.01	[0.78,	0.81]
λ	Labor efficiency wedge	N	0.0	0.5	1.45	1.46	0.04	[1.40,	1.54]
ϕ	Leverage	U	3.5	0.87	4.89	4.94	0.06	[4.81,	4.98]
ρ_a	Neutral technology growth	B	0.4	0.2	0.84	0.85	0.01	[0.83,	0.85]
$\sigma_a^{(0)}$		G	0.433	0.433	0.28	0.25	0.02	[0.22,	0.29]
$\sigma_a^{(1)}$		G	0.177	0.177	0.00	0.03	0.04	[0.00,	0.10]
$\sigma_a^{(4)}$		G	0.177	0.177	0.18	0.19	0.04	[0.16,	0.21]
ρ_{is}	Marginal efficiency of investment	B	0.6	0.2	0.85	0.85	0.01	[0.83,	0.86]
$\sigma_\omega^{(0)}$		G	3.031	3.031	0.16	0.11	0.02	[0.08,	0.17]
$\sigma_\omega^{(1)}$		G	1.237	1.237	0.07	0.07	0.01	[0.05,	0.09]
$\sigma_\omega^{(4)}$		G	1.237	1.237	0.16	0.19	0.01	[0.15,	0.21]
(log) Likelihood					-1822.5	-1833.4			
(log) Posterior					-1830.4	-1841.6			

Table 1: **Prior densities and posterior estimates for the baseline model.** Calibrated coefficients: $\beta = 0.998$, $\delta = 0.025$, $\alpha = 0.34$, $\mu = 0.004$. The time unit is defined to be one quarter. Relative to the text, the standard deviations of the innovations (σ) are scaled by 100. Median and posterior percentiles are from 2 chains of 130,000 draws generated using a Random Walk Metropolis algorithm. We discard the initial 30,000 draws. N stands for Normal, B–Beta, G–Gamma, U–Uniform. In the models with news, the priors are chosen so that the variance of each unanticipated shock equals 75% of the total variance of the corresponding disturbance.

Panel A: Share of Unconditional Variance Explained by Shocks

	Neutral technology			Investment specific technology		
	Unanticipated		Anticipated	Unanticipated		Anticipated
		one-quarter	four-quarter		one-quarter	four-quarter
Series \Shock						
Output	0.14	0.03	0.19	0.09	0.10	0.45
	[0.11, 0.17]	[0.00, 0.09]	[0.10, 0.25]	[0.05,0.19]	[0.05,0.16]	[0.38,0.51]
Consumption	0.46	0.02	0.26	0.03	0.02	0.20
	[0.39, 0.52]	[0.00, 0.10]	[0.12, 0.32]	[0.01,0.07]	[0.01,0.03]	[0.15,0.24]
Investment	0.04	0.03	0.14	0.11	0.12	0.56
	[0.03, 0.05]	[0.00, 0.07]	[0.11, 0.20]	[0.06,0.22]	[0.06,0.21]	[0.49, 0.63]
Hours	0.14	0.02	0.13	0.10	0.05	0.56
	[0.14, 0.22]	[0.00, 0.05]	[0.11, .17]	[0.06,0.16]	[0.02,0.09]	[0.46, 0.59]
Price-dividend ratio	0.49	0.05	0.42	0.02	0.00	0.02
	[0.41, 0.58]	[0.00, 0.10]	[0.30, 0.50]	[0.01,0.05]	[0.00,0.01]	[0.01, 0.03]

Panel B: Share of Variance at Business cycle frequencies Explained by Shocks

	Neutral technology			Investment specific technology		
	Unanticipated		Anticipated	Unanticipated		Anticipated
		one-quarter	four-quarter		one-quarter	four-quarter
Series \Shock						
Output	0.40	0.06	0.28	0.03	0.02	0.22
	[0.09, 0.61]	[0.00, 0.12]	[0.02, 0.65]	[0.01,0.06]	[0.00,0.05]	[0.06,0.46]
Consumption	0.50	0.08	0.30	0.01	0.01	0.11
	[0.08, 0.62]	[0.00, 0.27]	[0.02, 0.52]	[0.00,0.04]	[0.00,0.02]	[0.02,0.31]
Investment	0.11	0.02	0.17	0.08	0.05	0.57
	[0.03, 0.28]	[0.00, 0.06]	[0.01, 0.32]	[0.03,0.18]	[0.02,0.11]	[0.37 0.73]
Hours	0.04	0.01	0.14	0.10	0.06	0.66
	[0.02, 0.07]	[0.00, 0.03]	[0.01, 0.26]	[0.04,0.21]	[0.02,0.13]	[0.50, 0.80]
Price-dividend ratio	0.47	0.06	0.42	0.01	0.00	0.05
	[0.27, 0.66]	[0.00, 0.18]	[0.03, 0.65]	[0.00,0.02]	[0.00,0.01]	[0.02, 0.08]

Table 2: **Variance decomposition in the news model.** Share of variance explained by anticipated and unanticipated disturbances. Panel A shows the unconditional variance decomposition. Panel B shows the variance at business cycle accounted by the different shocks. Business cycle frequencies correspond to periodic components with cycles between 6 and 32 quarters. The decomposition is obtained using the spectrum of the DSGE model and an inverse first difference filter for output, consumption, investment and wages to reconstruct the levels. The spectral density is computed from the state space representation of the model with 5000 bins for frequencies covering that range of periodicities. Medians need not add up to one.

	Standard deviation				Autocorrelation			
		Baseline Model				Baseline Model		
Series	Data	Median	[5th,	95th]	Data	Median	[5th,	95th]
Output growth	0.97	1.20	[1.09,	1.33]	0.37	0.21	[0.08,	0.33]
Consumption growth	0.55	0.65	[0.58,	0.74]	0.20	0.23	[0.10,	0.36]
Investment growth	2.43	5.89	[4.47,	6.57]	0.53	0.02	[-0.06,	0.16]
Hours	4.73	3.48	[2.79,	4.79]	0.98	0.90	[0.84,	0.93]
Price-dividend ratio	0.42	0.27	[0.19,	0.37]	0.98	0.96	[0.92,	0.98]
	Standard deviation relative to output				Correlation with output growth			
		Baseline Model				Baseline Model		
Series	Data	Median	[5th,	95th]	Data	Median	[5th,	95th]
Consumption growth	0.56	0.54	[0.49,	0.61]	0.51	0.62	[0.52,	0.70]
Investment growth	2.49	4.86	[3.72,	5.15]	0.67	0.95	[0.94,	0.97]
Hours	4.85	2.89	[2.37,	3.58]	0.10	0.37	[0.28,	0.46]

Table 3: **Standard deviations and correlations for observable variables in the baseline model.** For each parameter draw, we generate an artificial sample of the observable variables with same length as our dataset (263 observations) after discarding 50 initial observations.

A VAR representation of the shocks

The dynamics of total factor productivity growth $x_{1,t}$ and investment sector productivity $x_{2,t}$ can be written as a first order vector autoregressive system. For parsimony we present the special case with unanticipated, one- and four-quarter anticipated total factor productivity shock. The general case can be derived analogously. The dynamics

$$x_{1,t} = (1-\rho_1)\mu_1 + \rho_1 x_{1,t-1} + \varepsilon^0_{1,t} + \varepsilon^1_{1,t-1} + \varepsilon^4_{1,t-4}$$

can be written as

$$x_{t+1} = H_0 + H_1 x_t + H_2 \epsilon_{t+1},$$

where:

$$x_t = \begin{pmatrix} x_{1,t} \\ \varepsilon^1_{1,t} \\ \varepsilon^4_{1,t} \\ \varepsilon^4_{1,t-1} \\ \varepsilon^4_{1,t-2} \\ \varepsilon^4_{1,t-3} \end{pmatrix}, \; H_0 = \begin{pmatrix} (1-\rho_1)\mu_1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \; H_1 = \begin{pmatrix} \rho_1 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix}, \; H_2 = \begin{pmatrix} \sigma_a^{(0)} & 0 & 0 \\ 0 & \sigma_a^{(1)} & 0 \\ 0 & 0 & \sigma_a^{(4)} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}.$$

B Inducing stationarity and calculating the steady state

Since the TFP process A_t has a unit root our economy is growing. For all the variables X_t inheriting the unit root define $\tilde{X}_t$ as $\tilde{X}_t = \dfrac{X_t}{A_{t-1}}$ and $\tilde{V}_t = V(\tilde{K}_t, \tilde{A}_t, x_{i,t})$, $i > 1$. Note that the value function is homogeneous of degree one in K_t and A_t (simply observe that all equations in the model are). Equilibrium conditions can be summarized as follows:

$$E_t\left(M_{t+1} \frac{\alpha\left(\frac{\tilde{A}_t N_t}{\tilde{K}_t}\right)^{1-\alpha} + q_{t+1}\left(1-\delta+\omega_{t+1}(1-\zeta)\, g\left(\frac{\tilde{I}_{t+1}}{\tilde{K}_{t+1}}\right)\right)}{q_t} \right) = 1,$$

$$\tilde{V}_t^{1-1/\psi} = \left[\tilde{C}_t (1-N_t)^\eta\right]^{1-1/\psi} + \tilde{A}_t^{1-\frac{1}{\psi}} \beta \left[E_t\left(\tilde{V}_{t+1}^{1-\gamma}\right)\right]^{\frac{1-1/\psi}{1-\gamma}},$$

$$\tilde{A}_t \tilde{K}_{t+1} = (1-\delta)\tilde{K}_t + \omega_t g\left(\frac{\tilde{I}_t}{\tilde{K}_t}\right)\tilde{K}_t,$$

$$\eta \frac{\tilde{C}_t}{1-N_t} = (1-\alpha)\frac{\tilde{Y}_t}{N_t} h\left(\tilde{Y}_t\right),$$

$$\tilde{Y}_t = \left(\tilde{A}_t N_t\right)^{1-\alpha} \tilde{K}_t^\alpha,$$

$$\tilde{C}_t + \tilde{I}_t = \left(\alpha + (1-\alpha)\, h\left(\tilde{Y}_t\right)\right)\tilde{Y}_t,$$

$$\ln \tilde{A}_t = x_{1,t} \ ,$$

$$\ln \omega_t = x_{2,t} \ ,$$

$$x_{t+1} = H_0 + H_1 x_t + H_2 \epsilon_{t+1},$$

$$PD_t = E_t \left(M_{t+1} \tilde{A}_t^{\phi} \left(\frac{\tilde{C}_{t+1}}{\tilde{C}_t} \right)^{\phi} e^{(1-\phi)\mu} \left(PD_{t+1} + 1 \right) \right),$$

where

$$M_{t+1} = \beta \tilde{A}_t^{-1/\psi} \left(\frac{\tilde{V}_{t+1}}{E_t \left(\tilde{V}_{t+1}^{1-\gamma} \right)^{\frac{1}{1-\gamma}}} \right)^{1/\psi - \gamma} \left(\frac{\tilde{C}_{t+1}}{\tilde{C}_t} \right)^{-1/\psi},$$

$$q_t = \frac{1}{\omega_t g' \left(\frac{\tilde{I}_t}{\tilde{K}_t} \right)}.$$

The non-stochastic steady state is given by:

$$\tilde{K} = \tilde{A} N \left(\frac{\beta^{-1} \tilde{A}^{1/\psi} - 1 + \delta)}{\alpha} \right)^{\dfrac{1}{\alpha - 1}},$$

$$\tilde{V} = \left(\frac{\left[\tilde{C} \left(1 - N \right)^{\eta} \right]^{1 - 1/\psi}}{1 - \beta \tilde{A}^{1 - \frac{1}{\psi}}} \right)^{\frac{1}{1 - \frac{1}{\psi}}}$$

$$\tilde{C} = \tilde{Y} - (\tilde{A} - 1 + \delta)) \tilde{K},$$

$$\eta \frac{\tilde{C}}{1 - N} = \left(1 - \alpha \right) \frac{\tilde{Y}}{N},$$

$$\tilde{Y} = \left(\tilde{A} N \right)^{1-\alpha} \tilde{K}^{\alpha},$$

$$\tilde{A} = \exp(x_1),$$

$$x = \left(I - H_1 \right)^{-1} H_0,$$

$$PD = \frac{\beta \tilde{A}^{1-1/\psi}}{1 - \beta \tilde{A}^{1-1/\psi}}.$$

C Perturbation Solution

An approximate analytical solution to the model can be easily found using perturbation methods. Following the notations laid out in Schmitt-Grohe and Uribe (2004) we write the system of equilibrium conditions that recursively define the model as

$$E_t f \left(y_{t+1}, y_t, x_{t+1}, x_t \right) = 0,$$

where y_t is the vector of control variables and x_t is a vector containing state variables (notice that the notation in this sub-section are independent of the rest of the paper). As it is standard in macroeconomics, we rewrite the model in terms of log-transformed variables.

The solution is given by the equilibrium policy function for y_t and the laws of motion for x_t:

$$\begin{aligned} y_t &= g(x_t, \sigma), \\ x_{t+1} &= h(x_t, \sigma) + \sigma \xi_v \nu_{t+1}, \end{aligned}$$

where σ is a parameter scaling the size of uncertainty. At the non-stochastic steady state $\sigma = 0$ (we set it equal to 1 otherwise). We define the non-stochastic steady state as vectors $(\bar{x}; \bar{y})$ such that

$$f(\bar{y}, \bar{y}, \bar{x}, \bar{x}) = 0$$

We expand the functions g and h around the $\sigma = 0$ and $x_t = \bar{x}$ point. For estimation purposes we approximate the functions $g(x_t, \sigma)$ and $h(x_t, \sigma)$ to first order. This allows us to obtain linearized dynamics of macroeconomic and financial variables. To derive risk adjustments required to compute asset pricing moments we use a second order approximation.

Schmitt-Grohe and Uribe (2004) show that the following terms of the Taylor expansion are zero i.e. $g_\sigma = h_\sigma = g_{\sigma x} = h_{\sigma x} = 0$.
$g_\sigma = h_\sigma = 0$ implies that the first order approximation is not affected by the volatility of the shock and produces no adjustment for risk.
$g_{\sigma x} = h_{\sigma x} = 0$ implies that a second-order approximation can only produce constant risk premia. Furthermore, the risk aversion parameter γ does not affect the non-stochastic steady state values. Neither does it enter the expressions for h_x or h_{xx} evaluated at the non-stochastic steady-state. In other words, up to the second order, risk aversion matters for the difference between the stochastic steady state and the non-stochastic steady state but not for the dynamics of the variables.

D Data description

We follow Schmitt-Grohé and Uribe (2012) and construct the macroeconomic observable variables used in the estimation as:

1. Real Gross Domestic Product, BEA, NIPA table 1.1.6., line 1, billions of chained 2000 dollars seasonally adjusted at annual rate. Downloaded from www.bea.gov.

2. Gross Domestic Product, BEA NIPA table 1.1.5., line 1, billions of dollars, seasonally adjusted at annual rates.

3. Personal Consumption Expenditure on Nondurable Goods, BEA, NIPA table 1.1.5., line 4, billions of dollars, seasonally adjusted at annual rate. Downloaded from www.bea.gov.

4. Personal Consumption Expenditure on Services, BEA NIPA table 1.1.5., line 5, billions of dollars, seasonally adjusted at annual rate. Downloaded from www.bea.gov.

5. Gross Private Domestic Investment, Fixed Investment, Nonresidential, BEA NIPA table 1.1.5., line 8, billions of dollars, seasonally adjusted at annual rate. Downloaded from www.bea.gov.

6. Gross Private Domestic Investment, Fixed Investment, Residential, BEA NIPA table 1.1.5., line 11, billions of dollars, seasonally adjusted at annual rate. Downloaded from www.bea.gov.

7. Civilian Noninstitutional Population Over 16, BLS LNU00000000Q. Downloaded from www.bls.gov.

8. Nonfarm Business Hours Worked, BLS, PRS85006033, seasonally adjusted, index 1992=100. Downloaded from www.bls.gov.

9. GDP Deflator = (2) / (1).

10. Real Per Capita GDP = (1) / (7).

11. Real Per Capita Consumption = [(3) + (4)] / (9) / (7).

12. Real Per Capita Investment = [(5) + (6)] / (7) / (9).

13. Per Capita Hours = (8) / (7).

With regard to the financial variables, we take stock return and dividend data from CRSP and convert to real terms using the CPI. In particular we use data on the value-weighted market return (NASDAQ, NYSE, AMEX), with and without dividend capitalization to obtain our dividend-price ratio defined as D_t/P_t.

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