News Shocks and Asset Prices*

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Abstract

We estimate a parsimonious RBC model with anticipated productivity shocks (news), and study its asset pricing implications. A combination of news shocks and low wealth effects (i) allows the model to reproduce the lead of stock-market returns and valuation ratios over macroeconomic aggregates at business cycle frequencies, and (ii) creates expected, as opposed to realized, consumption growth risk which leads to higher equity risk premium. In addition, we identify news shocks about future technology using a structural VAR approach, and we feed these shocks into the model. We find that anticipated shocks play an important role in explaining the fluctuations of stock-market valuation ratios.

Keywords : Anticipated Shocks, Asset Prices, Aggregate Fluctuations, Recursive Preferences, Perturbation Methods, DSGE Model Estimation

JEL Classification : G12, E32, E21, C63

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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 are forward looking, it is natural to extend the scope of the analysis and relate news shocks to the properties of stock-market returns and valuation ratios. In this paper we estimate a simple production-based asset pricing model with anticipated shocks using both macroeconomic and financial data, and analyze its implications. First, we find that news shocks allow the model to explain key macro-finance co-movements, notably the lead of stock-market returns and valuation ratios over output, investment, and consumption at business cycle frequencies. Second, we find that news shocks create expected, as opposed to realized, consumption growth risk which leads to higher equity risk premia, for a given volatility of consumption growth.

Our setup is a standard RBC model augmented along two dimensions: Epstein-Zin-Weil preferences, that separate representative agent's elasticity of intertemporal substitution (EIS) from the inverse of her relative risk aversion (RRA), and anticipated total factor productivity (TFP) shocks.[2] Our estimates imply a high EIS and a high volatility of TFP shocks anticipated one and four quarters ahead relative to TFP surprises. The model is able to explain the salient features of the data through a combination of these two features. Given weak wealth effects implied by high EIS positive news do not lead to a large fall in investment: they are not 'consumed away' immediately, as would be implied by a real business cycle model where households have constant RRA utility and low EIS. Instead, on-impact responses of consumption and investment to news are moderate and lead to predictable growth in consumption, investment and output over the

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

[2]It is important to distinguish between news and noise. The former are actual changes in fundamentals anticipated one or several periods ahead. The latter are temporary errors. Recent work in macroeconomics looks at the respective roles of news and noise shocks for aggregate fluctuations. See for instance Blanchard, L'Huillier, and Lorenzoni (2009). This paper deals with the asset pricing implication of news only. Expectations can be revised - good news about productivity two quarters ahead can potentially be offset by bad one quarter ahead news the following period - but agents are correct on average.

following quarters. This in turn implies that stock-market returns and valuation ratios lead consumption, output and investment growth, consistently with the data.[3] Standard production economy models without news shocks do not generate the lead of asset returns over macro quantities and imply a high contemporaneous correlations between the two. Finally, under recursive preferences expected, as opposed to realized, consumption growth risk increases risk premia without increasing the realized volatility of consumption growth.

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. We use classical maximum likelihood (ML) 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-Grohe and Uribe (2012), but in addition to macroeconomic variables includes stock-market valuations in the estimation. We also compare our structural estimation results to the identification of news shocks based on a VAR approach proposed by Barsky and Sims (2011). We find that the impulse responses implied by the estimated model are consistent with VAR-identified responses. Finally, when we feed the VAR-identified news shocks into the model, it is able to match well the historical time series of the price to dividend (PD) ratio.

Our macroeconomic model with production allows us to gain a new perspective on the long run-risk strand in consumption-based asset pricing literature that goes back to Bansal and Yaron (2004) work. Long-run risk models rely on exogenously specified variation in conditional means and volatilities to address major asset pricing puzzles. In this

[3] See Backus, Routledge, and Zin (2007) for evidence on lead and lag macro-finance correlations in the data.

paper these features in consumption growth arise as an endogenous response to macroeconomic shocks. In addition, we can evaluate the performance of the model based not only on asset pricing moments but also aggregate macro-finance co-movements. Predictability in consumption growth is an essential element of long-run risk models. Because overall consumption growth in the data is not persistent, its predictable component is typically assumed to be very small but also highly persistent. This however implies counterfactual long-run predictability of consumption growth by PD ratios, as pointed out by Beeler and Campbell (2012). In contrast, in a model driven by news shocks GDP and consumption growth, while not persistent themselves, are largely predictable over the following quarters conditional on the additional latent state variables that describe agents information set. This is consistent with the up to four quarter lead of asset returns over the business cycle in the data.

We use perturbation methods to solve the model and implement ML estimation. 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.

Our paper is related to Kurmann and Otrok (2012), who show that news shocks are closely related to the changes in the slope of the term structure of interest rates. We do not consider the pricing of nominal bonds, and focus on stock-market returns and valuation ratios.

Our paper is also related to the growing production-based asset pricing literature. See Tallarini (2000), Kaltenbrunner and Lochstoer (2010), Croce (2013), Kung and Schmid (2013) to mention just a few contributions. Relative to these papers we propose an additional channel that affects both risk premia and macro-finance co-movements. Also, we take one more step in bringing the model to the data by estimating, rather than calibrating it.

Croce (2013) argues that TFP time series contain a small, highly persistent component. In other words, news shocks are shocks to the long-run productivity growth. We do not replicate the author's analysis based on Kalman filtering. However, the results based on Barsky and Sims (2011) identification approach suggest that news explain a significant amount of variation in TFP at the business cycle frequency.

The rest of the paper is organized as follows. Section 2 presents the model. Section 3 presents estimation methodology and results. Section 4 provides a discussion. Section 5 compares the structural estimation results to the ones obtained with a VAR approach. Finally, Section 6 concludes.

2 Model

Our setup is a standard RBC model augmented along two dimensions: anticipated productivity shocks and Epstein-Zin-Weil (see Epstein and Zin (1989), Epstein and Zin (1991) and Weil (1989)) preferences.

Preferences. The representative consumer maximizes a utility function defined recursively:

$$\underset{C_t}{Max} U_t,$$

where

$$U_t = \left(C_t^{1-1/\psi} + \beta (E_t(U_{t+1}^{1-\gamma}))^{\frac{1-1/\psi}{1-\gamma}} \right)^{\frac{1}{1-1/\psi}}.$$

Compared to CRRA utility this specification of preferences allows us to calibrate the EIS ψ independently from the coefficient of RRA γ.

Technology. The consumption good is produced according to a neoclassical production function

$$Y_t = A_t^{1-\alpha} K_t^{\alpha},$$

where K_t is the stock of capital, hours worked are constant and normalized to 1 and Y_t

is the output. A_t represents the TFP. The law of motion of capital is given by

$$K_{t+1} = (1-\delta)\, K_t + I_t,$$

where $I_t = Y_t - C_t$.

Shocks. The specification for the technology shocks is the key element of the model. Denote productivity growth as:

$$\ln A_t - \ln A_{t-1} = x_t^1.$$

We specify x_t^1 as autoregressive and subject to anticipated and un-anticipated innovations[4]

$$x_t^1 = (1-\rho)\mu + \rho x_{t-1}^1 + \sum_{j=0}^{J} \varepsilon_{t-j}^j. \tag{1}$$

ε_t^0 are date t productivity surprises. Innovations ε_{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 $J+1$ innovations that affect productivity immediately (ε_t^0) and in up to J periods ahead (ε_t^j). 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 being the first element of vector x_t, $\epsilon_t \sim N(0, I_{(J+1)\times(J+1)})$ and matrices H_0, H_1 and H_2 given in Appendix B.

Asset prices. Equilibrium conditions are presented in Appendix A. The equilibrium

[4] We borrow this specification from Schmitt-Grohe and Uribe (2012).

stochastic discount factor (SDF) is

$$M_{t+1}=\beta\left(\frac{V_{t+1}}{E_t\left(V_{t+1}^{1-\gamma}\right)^{\frac{1}{1-\gamma}}}\right)^{1/\psi-\gamma}\left(\frac{C_{t+1}}{C_t}\right)^{-1/\psi}, \tag{2}$$

where $V_t=\max_{C_t} U_t$. 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 $\left(\frac{V_{t+1}}{E_t\left(V_{t+1}^{1-\gamma}\right)^{\frac{1}{1-\gamma}}}\right)^{1/\psi-\gamma}$ 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.

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

$$E_t\left(M_{t+1}R_{i,t+1}\right)=1. \tag{3}$$

In particular one-period risk-free rate satisfies

$$R_{f,t}^{-1}=E_tM_{t+1}.$$

We follow a standard approach in finance literature and take the leveraged consumption claim as the model counterpart of the stock-market.[5] We assume that fluctuations in aggregate dividend growth around trend TFP growth are equal to the fluctuations in consumption growth around the same trend amplified by the leverage parameter λ:

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

In particular, when $\lambda=1$, the asset is simply the claim on aggregate consumption stream,

[5] 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 (2010) find that both risk premia and volatility are lower for the consumption claim compared to the stock-market.

or total wealth. $\lambda > 1$ is a reduced-form way to model leverage. Substituting the total return - the sum of dividend and capital gain - on the dividend claims in the asset pricing equation (3) provides us with a recursive definition of the PD ratio, that can be easily solved for using perturbation methods:

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

3 Estimation

We use classical ML methods to estimate a subset of the deep structural parameters of the model, in particular those defining the stochastic processes of anticipated and unanticipated innovations. The parameters that are not estimated are calibrated in a standard fashion.

3.1 Inducing Stationarity and Solution Method

The exogenous TFP process A_t displays a unit root and it is inherited by a subset of the endogenous variables of the model. We divide those variables by the lag of the TFP process and re-write the model in terms of stationary variables only. See Appendix C for details.

We then proceed to solve the model using familiar perturbation techniques (e.g., Schmitt-Grohe and Uribe (2004), Caldara, Fernandez-Villaverde, Rubio-Ramirez, and Yao (2012), Schmitt-Grohe and Uribe (2012)). For estimation purpose we compute a log-linear approximation to the equilibrium dynamics of the model. Notice that simple simple log-linearization is insufficient to derive the risk adjustments for the financial variables. In order to analyze the asset pricing moments of the model we use a second order perturbation solution of the log-transformed model. See Appendix D for additional details.

3.2 Calibrated Parameters

Panel A of Table 1 presents the values assigned to the calibrated parameters. We use values for the production technology that are standard in the macro literature, taken from Boldrin, Christiano, and Fisher (2001). In particular, the capital share (α) is 0.34, the quarterly depreciation rate (δ) is 0.025, and the quarterly log technology growth rate (μ) is 0.4%. In addition, we set we set the discount factor (β) at 0.998, a value commonly used in related studies.

3.3 Classical Maximum Likelihood Estimation

The time unit is defined to be one quarter. Given the linearized equilibrium dynamics of the model, it is straightforward to evaluate the likelihood function $L(Y \mid \Theta)$, where Y is the data sample and Θ, is the vector of parameters to be estimated. The vector of estimated parameters, Θ, contains the parameters defining the stochastic process for anticipated and unanticipated innovations, namely, ρ and σ^j, $j = 0, 1, 2, 3, 4$. In addition, the parameter vector Θ includes the EIS (ψ) and leverage (λ).

We estimate the model on U.S. quarterly data ranging from 1947:Q2 to 2012:Q4. The data include three time series: the growth rates of per capita real GDP, the growth rates of real consumption, and the PD ratio. 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)). For computational convenience, we assume that output growth is measured with error: we set the standard deviation of the measurement error as 20% of that of the observation.[6] Appendix E describes the data sources and construction of variables used for the empirical analysis.

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

[6]The interest reader is referred to An and Schorfheide (2007) for the role of measurement errors in the analysis of DSGE models.

parameter vector Θ by applying the test proposed by Iskrev (2010). 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 ML estimation procedure captures the true parameter values reasonably well.

We note that the coefficient of RRA (γ), that has to be determined separately from the EIS, does not appear in the log-linearized dynamics of the variables. See Appendix D. Therefore, the only moment that has to be adjusted for risk and agent's attitude towards risk is the unconditional mean of the PD ratio. We use the second order approximation of the model and choose γ to match this moment.[7]

Panel B of Table 1 displays the result of the estimation. From an economic point 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 (ϵ_t^4) about future changes in the TFP, its volatility being comparable to the unanticipated one. On the other hand the two, and three quarters anticipated components are not statistically different from zero at any standard confidence levels. 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. Our estimate of the EIS parameter ψ turns out to be significantly greater than one: in Section 4 we discuss at length the mechanism that drives such a result.

Panel A of Table 2 reports business cycle moments (standard deviations and correla-

[7] Malkhozov and Shamloo (2013) describe a method to compute risk adjustments based on the log-linear approximation of the model. This approach allows adjustments for risk to be included in the estimation directly. For the case where we consider the valuation ratios of aggregate stock-market only, it is equivalent to the simpler approach adopted in this paper.

tions) in the estimated model.[8] For comparison, the table also shows the corresponding empirical second moments calculated over the sample 1947:Q2 to 2012:Q4. In the data consumption is less volatile than output, and investment is more volatile than output. The model is significantly close to the data along these dimensions. In particular, it replicates the observed levels of volatility in investment, output, and slightly over-predicts the volatility in consumption.[9] The model also captures well the autocorrelations (not reported) and contemporaneous correlations of macroeconomic variables: : Notably the model-implied first order autocorrelation of consumption growth is 0.18, as in the data.

Turning to asset pricing implications, Panel B of Table 2 shows that the estimated news model is able to match the financial moments well. In particular the model generates an equity premium in line with the data, of about 5.37% per year. This latter fact is noteworthy given a coefficient of RRA of only 4.28. The model replicates the observed levels of volatility in the financial variables: Importantly, the model matches the low volatility of short-term interest rates (0.4% vs. 1.1% in the data). Finally our news model does a good job of matching the first-order autocorrelation of dividend-price (0.96 in the model vs. 0.97 in the data).

In all, our likelihood-based estimates of the news model provide a good stylized description of the salient features of the data and point to anticipated shocks in TFP as an important source of economic and financial fluctuations. In the next section we inspect the mechanisms in more detail.

4 Discussion

In this section we discuss the main channels through which news shocks affect macroeconomic and asset pricing moments of the estimated model.

[8] The population second moments are computed using the point estimates of the structural parameters obtained from the maximum likelihood.

[9] The model implied volatility of consumption growth is about 1.4%: This value, although greater than the 1.1% obtained in the post-war sample, is still lower than the consumption volatility over the longer annual sample 1930-2012, which is greater than 2%.

4.1 Correlation between macroeconomic variables

In line with the data, the model implies correlations between consumption, investment, and output that are positive, but significantly lower than 1. This is true for the correlation between consumption and investment in particular. In contrast, the co-movement in all macroeconomic variables is near-perfect when we shut down the news shocks. News allow to de-couple the movements in consumption, output and investment because anticipated productivity shocks do not relax the current resource constraint of the economy. Agents face a trade-off between consumption and investment. However, before anticipated productivity shocks realize, agents cannot increase one without decreasing the other.[10]

4.2 EIS and the lead of financial over macroeconomic variables

Using the estimated parameters, notably the EIS, the model matches the lead of stock-market returns and PD ratios over output, investment, and, to a lesser extent, consumption growth. The positive correlation between the stock-market returns and subsequent changes in macroeconomic variables has been documented by Backus, Routledge, and Zin (2007) among others. Figure 1 reports cross-correlations between financial and macroeconomic variables in the model. In this section we argue that both news shocks and high EIS are necessary for the model to produce this result: without news the lead cross-correlations are close to zero, with news but without high EIS the correlations are negative.

[10] In a more general setting agents could increase consumption without reducing investment by adjusting other variables such as hours worked. However, Barro and King (1984) and Cochrane (1994) emphasize that in a standard neoclassical setting the wealth effect of good news about future productivity causes households to desire more consumption of both goods and leisure and that this is the key challenge for news driven business cycle Thus optimal labor choice can make comsumption-investment trade-off more and not less stringent. Supporting this view Barsky and Sims (2011) provide evidence of the negative response of hours to favorable productivity news in the data. In addition, Jaimovich and Rebelo (2009) illustrate the theoretical challenge of generating a joint postitive response of consumption, investment, and hours to good news about future TFP by building what seems to be a minimal RBC model able to achieve this result. The model relies on an interplay between Greenwood, Hercowitz, and Huffman (1988) preferences, a particular form of investment adjustment costs, and variable capital utilization. Endogenizing labor in production-based asset pricing models is an interesting avenue for future research, not only in relation to news shocks, but also more generally.

The estimated value for the EIS parameter $\psi = 1.494$ (see again Table 1 - Panel B) is greater than 1 implying only a weak wealth effect. In other words, agents respond to actual or expected productivity improvements by only a small immediate increase in consumption. Note that the estimated value is consistent with the one typically used to calibrate consumption-based and RBC long-run risk models. See Bansal and Yaron (2004) and Kaltenbrunner and Lochstoer (2010) among others. Why high EIS is important for the model to match the properties of the data? In the next section we show that impulse responses of consumption and investment to news shocks identified using VAR methodology are consistent with a moderate wealth effect and hence a high value for the EIS. The properties of financial variables in the model provide a more direct way to see the importance of high EIS. The model with news shocks and low ψ implies a negative correlation between returns and PD ratios, and subsequent growth in output, consumption, and investment. This happens because when wealth effects are strong, agents immediately 'consume away' anticipated increases in productivity. Figure 2 illustrates this point by comparing the lead and lag cross-correlations between PD ratio and investment growth for high and low values if the EIS.

Anticipated changes in productivity, combined with high EIS, are a natural channel to account for the lead of asset prices over macroeconomic quantities. Asset prices are forward looking and incorporate expected changes in the fundamentals immediately, while high EIS ensures moderate on impact response of consumption to news. In contrast, without news shocks, financial variables are counterfactually near-perfectly correlated with contemporaneous changes in macroeconomic quantities.

4.3 News shocks and risk premia

The overall level of equity risk premium as well as the volatility of stock market returns implied by the model depends on the estimated leverage parameter $\lambda = 6.14$.[11] The pa-

[11] It can be shown that leverage increases the volatility of PD ratio and stock-market returns by a factor of $\frac{\lambda - 1/\psi}{1 - 1/\psi}$.

rameter measures both operational and financial leverage. The value is situated towards the high end of the range used in prior literature. For example, the model of Bansal and Yaron (2004) uses leverage parameters of three and five. The ratio of dividend growth volatility to consumption growth volatility in postwar U.S. data is well in excess of 6 (see Beeler and Campbell (2012)). Note that at the same time the estimated RRA parameter $\gamma = 4.28$ is very conservative.

We are specifically interested in the effect of news shock on asset pricing moments. Compared to a version of our model where we allow for TFP surprises only (as e.g. in Kaltenbrunner and Lochstoer (2010)), the equity risk premium in the estimated model is higher by 1.20%, keeping the volatility of consumption growth constant (see Table 2 - Panel B).[12]

Why do news shocks matter for risk premia? When EIS is high, productivity news translate to a large extent into shocks to expected, as opposed to realized, consumption growth. As can be seen from equation (2) innovations to expected future consumption growth enter the stochastic discount factor through the value function term $\left(\frac{V_{t+1}}{E_t\left(V_{t+1}^{1-\gamma}\right)^{\frac{1}{1-\gamma}}}\right)^{1/\psi-\gamma}$. As a result, when $1/\psi \neq \gamma$, shocks to expectations are priced, which increases the market prices of risk. At the same time expectation shocks tend to offset each other and therefore do not increase the volatility of realized consumption growth significantly. This leads to higher risk premia for a given volatility of consumption and dividend growth.

While the effect of news shocks on equity risk premium is sizeable, it constitutes only a quarter of the total premium in the model. We argue that our analysis might underestimate the importance of news for asset prices. There are two sources of variation in expected consumption growth in the model, both contributing to high risk premia. First, as shown in Kaltenbrunner and Lochstoer (2010), in a basic RBC model with high

[12]The 1.2% premium on the one- and four-quarter news, is consistent with the findings in Ortu, Tamoni, and Tebaldi (2013). The authors document a premium between 1% and 2% on the component of consumption growth with a yearly half-life, (see Tables 9 and 10 in their paper). Importantly, the shocks to such a component impact consumption 4 quarters from now, similarly to our four-quarter anticipated shocks.

EIS consumption growth has an endogenous persistent component, in other words long-run risk. Second, as described above, news shocks introduce predictability at business cycle frequency that is not driven by persistence in the consumption process: consumption growth is predictable conditional on agents' information set, but not its own lags. The difference between news and long-run risk is important because long-run risk models imply counterfactual long-run predictability of consumption growth by PD ratios. See Beeler and Campbell (2012). This point is well illustrated by the lower panel on Figure 1: A model with endogenous long-run risk implies that both lead and lag correlations between PD ratio and consumption growth are high and decay only slowly with horizon. News shocks do not increase the overall level of correlations, but instead create a lead effect. Unfortunately, the two mechanisms cannot be disentangled in our simple model because both are controlled by the EIS: When EIS is high agents delay the increase in consumption until expected productivity improvements realize, but also choose to change consumption only progressively in response to realized changes in productivity. As a result it is not possible to increase the contribution of news without at the same time counterfactually increasing consumption growth persistence and its long-run predictability by financial variables.

5 Comparison with VAR-identified news shocks

In this section we further evaluate the contribution of anticipated technology shocks to business-cycle fluctuations in asset prices. However instead of simulating artificial data, we will feed our model actual news shock estimated from a vector autoregression (VAR) model. It is well known that the presence in a model of innovations with multi-period anticipation horizons 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. However we show that in the context of a single source of uncertainty our employed strategy identifies a single anticipated innovation which turns out to be a linear combination of the true anticipated innovations in total factor productivity.

Specifically, we identify a news shock about future innovations to TFP as in Barsky and Sims (2011). Barsky and Sims (2011) extend the forecast error variance (FEV) maximization approach of Uhlig (2003), and identify a TFP news shock directly as the innovation that accounts for most of the forecast error variance of TFP over a 10-year horizon but has no contemporaneous effect on TFP. This strategy, which is consistent with Beaudry and Portier (2006) original idea that TFP is driven by a contemporaneous component and a slowly diffusing news component, has the advantage that it does not rely on additional zero restrictions about other non-news shocks and it does not make any restriction about common trends in the different VAR variables. This is important since the interplay of long-run restrictions and cointegration assumptions in Beaudry and Portier (2006) raises important identification problem as pointed out by Kurmann and Mertens (2013).

The crucial assumptions for Barsky and Sims (2011) approach to be valid are that TFP is well-described by an exogenous process in two orthogonal innovations, a surprise and an anticipated one. We show next that applying the Barsky and Sims (2011) approach to simulated data from our model with four anticipated news, yields an identified news which is a linear combination of the true underlying structural news shocks. The weight on the j-period anticipated shock is equal to the ratio of its variance to the total variance of the shocks, ie. $w^j = \frac{\sigma_j^2}{\sigma_1^2+\sigma_2^2+\sigma_3^2+\sigma_4^2}$. We generate one thousand different data sets with a number of observations corresponding to the sample size in our estimation. A VAR featuring log technology, log consumption, log output and stock prices is estimated on each generated data set. The systems are estimated in levels and include two lags of each variable. Fig. 3 depicts both theoretical and estimated impulse responses averaged over the simulations to a news shock that technology will be permanently higher. The theoretical responses are vertical bars and the average estimated responses over the simulations are depicted by solid black. The theoretical response is obtained by a combination of the anticipated shocks. The shaded gray areas are the 95% confidence bands from the simulations.

A number of features from the simulations stand out. The estimated empirical impulse responses are roughly unbiased on impact and for most horizons thereafter.[13] The estimated responses to a news shock are only slightly downward biased at long horizons, and the estimated dynamics are very close to the true dynamics at all horizons. The median correlation between the identified and true weighted combination of news shock is 0.88. Figure 4 shows that a regression of the identified news shocks on the true underlying anticipated innovations in the model, yields loadings close to the contribution of each shock to the total variance of anticipated news.

Relying on the fact that a VAR approach can identify a linear combination of the true underlying shocks, we now extract the single anticipated innovation in total factor productivity from the data. Compared to the previous exercise we consider a larger VAR system. In addition to the four variables in the benchmark system, we also include a measure of hours and inflation. The reason for including these additional variables is that, as shown in Barsky and Sims (2011), these variables in the system help in the identification of the news shock. Figure 5 shows the estimated impulse responses of TFP, consumption, output, and prices to the identified news shock[14] along with theoretical responses. The shaded areas are the 95% confidence bands from the bias-corrected bootstrap procedure of Kilian (1998). The responses are standard (see Barsky and Sims (2011)). Relative to the VAR identification, theoretical impulse responses imply a stronger effect of news on macroeconomic variables, especially at long horizon. This is because our news model with high EIS also contains an endogenous long-run risk component. The theoretical and VAR-estimated responses of stock prices to news are very close, highlighting the importance of asset prices for the identification of news shocks.

[13] A favorable news shock leads to rising consumption but falling investment on impact in the model. After impact, the aggregate variables track movements in technology. The empirical identification captures these features quite well.

[14] The system is estimated in the levels of all variables. The system features two lags in accord with the selection of the Schwartz Information Criterion. The truncation horizon in the identification problem is set at H=40.

Figure 6 presents the model's prediction for the PD ratio, together with the actual PD ratio from the S&P500 index. We also consider an adjusted price-divided ratio, which accounts for potential shifts in their long-run mean (see Lettau and VanNieuwerburgh (2008) and Favero, Gozluklu, and Tamoni (2011)): this allows us to focus on the cyclical fluctuations in the series (rather than low frequency changes) which we are aiming at explaining in this paper. We emphasize that the model line on the graph is produced by feeding it with the identified news and surprise shock. The surprise technology shock is identified as the reduced form innovation in TFP orthogonal to the identified news.

The correlation between the model implied PD ratio and the data is about 46%. If we focus on the detrended financial ratio series, the correlation raises to 57%. To the evaluate the importance of news relative to surprise shock, we repeat the exercise by setting to zero the anticipated innovations: In this case the correlation drops significantly to 20% (15% for the adjusted PD ratio). Overall our news model accounts for both cyclical and longer-term fluctuations in stock prices, and the anticipated component of the technology shocks plays a major role.

6 Conclusion

In this paper we document the role of anticipated productivity shocks in the asset pricing context. We take an additional step in bringing the model to the data by estimating it using both macroeconomic and financial data, rather than calibrating it. The estimated news model provides a good stylized description of the salient features of the data. It points to anticipated shocks in TFP as an important source of economic and financial fluctuations, and as a risk factor that contributes to the explanation of the equity risk premium.

Our paper can inform the ways in which exogenous consumption dynamics are modeled in consumption-based asset pricing literature: Predictability in consumption growth conditional on the additional variables of agent's information can lead to higher market prices of risk without counterfactual long-range predictability of consumption by asset prices which is typically implied by models with a highly persistent component in consumption growth.

Endogenizing labor in a production-based asset pricing model with news is an interesting avenue for future research. The ability of the model driven by news shocks to explain the cross-section of asset returns and valuations is another interesting topic for future work.

References

An, S., and F. Schorfheide (2007): "Bayesian Analysis of DSGE Models," *Econometric Reviews*, 26(2-4), 113–172.

Backus, D. K., B. R. Routledge, and S. E. Zin (2007): "Asset Prices in Business Cycle Analysis," *Working Paper*.

Bansal, R., and A. Yaron (2004): "Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles," *Journal of Finance*, 59(4), 1481–1509.

Barro, R., and R. G. King (1984): "Time Separable Preferences and International Substitution Models of Business Cycles," *Quarterly Journal of Economics*, 99(4), 817–839.

Barsky, R., and E. Sims (2011): "News Shocks and Business Cycles," *Journal of Monetary Economics*, 58(3), 273–289.

Basu, S., J. G. Fernald, and M. S. Kimball (2006): "Are Technology Improvements Contractionary?," *American Economic Review*, 96(5), 1418–1448.

Beaudry, P., and F. Portier (2006): "Stock Prices, News, and Economic Fluctuations," *American Economic Review*, 96(4), 1293–1307.

Beeler, J., and J. Y. Campbell (2012): "The Long-Run Risks Model and Aggregate Asset Prices: An Empirical Assessment," *Critical Finance Review*, 1(1), 141–182.

Blanchard, O. J., J.-P. L'Huillier, and G. Lorenzoni (2009): "News, Noise, and Fluctuations: An Empirical Exploration," *NBER Working Paper No. 15015.*

Boldrin, M., L. J. Christiano, and J. Fisher (2001): "Habit Persistence, Asset Returns, and the Business Cycle," *American Economic Review*, 91(1), 149–166.

Caldara, D., J. Fernandez-Villaverde, J. F. Rubio-Ramirez, and W. Yao (2012): "Computing Models with Recursive Preferences," *Review of Economic Dynamics*, 15(2), 188–206.

Cochrane, J. H. (1994): "Shocks," *Carnegie-Rochester Conference Series On Public Policy*, (41), 295–364.

Croce, M. M. (2013): "Long Run Productivity Risk: A New Hope for Production-based Asset Pricing?," *Working Paper*.

Epstein, L. G., and S. E. Zin (1989): "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework," *Econometrica*, 57(4), 937–969.

——— (1991): "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: An Empirical Analysis," *Journal of Political Economy*, 99(2), 263–286.

Favero, C. A., A. E. Gozluklu, and A. Tamoni (2011): "Demographic Trends, the Dividend-Price Ratio, and the Predictability of Long-Run Stock Market Returns," *Journal of Financial and Quantitative Analysis*, 46(5), 1493–1520.

Greenwood, J., Z. Hercowitz, and G. W. Huffman (1988): "Investment, Capacity Utilization, and the Real Business Cycle," *American Economic Review*, 78(3), 402–417.

Iskrev, N. (2010): "Local Identification in DSGE Models," *Journal of Monetary Economics*, 57(2), 189–202.

Jaimovich, N., and S. Rebelo (2009): "Can News about the Future Drive the Business Cycle?," *American Economic Review*, 99(4), 1097–1118.

Kaltenbrunner, G., and L. A. Lochstoer (2010): "Long-Run Risk through Consumption Smoothing," *Review of Financial Studies*, 23(8), 3141–3189.

Kilian, L. (1998): "Small-Sample Confidence Intervals For Impulse Response Functions," *Review of Economics and Statistics*, 80(2), 218–230.

Kung, H., and L. Schmid (2013): "Innovation, Growth, and Asset Prices," *Working Paper*.

Kurmann, A., and E. Mertens (2013): "Stock Prices, News, and Economic Fluctuations: Comment," *Working Paper*.

Kurmann, A., and C. Otrok (2012): "News Shocks and the Slope of the Term Structure of Interest Rates," *American Economic Review*, 103(6), 2612–2632.

Lettau, M., and S. VanNieuwerburgh (2008): "Reconciling the Return Predictability Evidence," *Review of Financial Studies*, 21(4), 1607–1652.

Lustig, H., S. Van Nieuwerburgh, and A. Verdelhan (2010): "The Wealth-Consumption Ratio," *Working Paper*.

Malkhozov, A., and M. Shamloo (2013): "Asset Prices in Affine Real Business Cycle Models," *Working Paper*.

Ortu, F., A. Tamoni, and C. Tebaldi (2013): "Long Run Risk and the Persistence of Consumption Shocks," *Review of Financial Studies*, 26(11), 2876–2915.

Schmitt-Grohe, S., and M. Uribe (2004): "Solving Dynamic General Equilibrium Models Using a Second-Order Approximation to the Policy Function," *Journal of Economic Dynamics and Control*, 28(4), 755–775.

——— (2012): "What's News in Business Cycles," *Econometrica*, 80(6), 2733–2764.

Tallarini, T. D. (2000): "Risk Sensitive Real Business Cycles," *Journal of Monetary Economics*, 45(3), 507–32.

Uhlig, H. (2003): "What Drives GNP?," *Working Paper*.

Weil, P. (1989): "The Equity Premium Puzzle and the Risk Free Rate Puzzle," *Journal of Monetary Economics*, 24(3), 401–21.

Appendix

A Equilibrium conditions

The social planner's problem is

$$V(K_t, x_t) = \max_{C_t} (U_t),$$

where V_t is the problem's continuation value or simply the value function. The maximization is subject to the resource constraint, the law of motion of capital and exogenous variables dynamics:

$$C_t + I_t = A_t^{1-\alpha} K_t^{\alpha},$$

$$K_{t+1} = (1-\delta)K_t + I_t,$$

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

The Bellman equation:

$$V_t = \max_{C_t} \left(C_t^{1-1/\psi} + \beta (E_t (V_{t+1}^{1-\gamma}))^{\frac{1-1/\psi}{1-\gamma}} \right)^{\frac{1}{1-1/\psi}}.$$

The first order conditions with respect to consumption:

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

The envelope condition with respect to capital:

$$V_{Kt} = \beta V_t^{\frac{1}{\psi}} E_t \left(V_{t+1}^{1-\gamma} \right)^{\frac{\gamma-1/\psi}{1-\gamma}} E_t \left(V_{t+1}^{-\gamma} V_{Kt+1} \left(1 - \delta + \alpha \left(\frac{A_t}{K_t} \right)^{1-\alpha} \right) \right).$$

Combining the two:

$$E_t \left[M_{t+1} \left(1 - \delta + \alpha \left(\frac{A_t}{K_t} \right)^{1-\alpha} \right) \right] = 1,$$

where M_{t+1} is the stochastic discount factor

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

B VAR representation of the shocks

We note that TFP growth

$$x_t^1 = (1-\rho)\mu + \rho x_{t-1}^1 + \sum_{j=0}^{J} \varepsilon_{t-j}^j$$

can be written as a first order vector autoregressive system

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

where (we consider the $J = 4$ case):

$$x_t = \begin{pmatrix} x_t^1 \\ \varepsilon_t^1 \\ \varepsilon_t^2 \\ \varepsilon_t^3 \\ \varepsilon_t^4 \\ \varepsilon_{t-1}^2 \\ \varepsilon_{t-1}^3 \\ \varepsilon_{t-1}^4 \\ \varepsilon_{t-2}^3 \\ \varepsilon_{t-2}^4 \\ \varepsilon_{t-3}^4 \end{pmatrix},$$

and

$$H_0 = \begin{pmatrix} (1-\rho)\mu \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \; H_1 = \begin{pmatrix} \phi & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix}, \; H_2 = \begin{pmatrix} \sigma^0 & 0 & 0 & 0 & 0 \\ 0 & \sigma^1 & 0 & 0 & 0 \\ 0 & 0 & \sigma^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma^3 & 0 \\ 0 & 0 & 0 & 0 & \sigma^4 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}.$$

C 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 $\tilde{V}_t = V(\tilde{K}_t, \tilde{A}_t, x_t^{(-1)})$. Since the value function is homogeneous of degree one in K_t and A_t (simply observe that all equations in the model are), we have:

$$V(K_t, A_t, x_t^{(-1)}) = A_{t-1} V\left(\frac{K_t}{A_{t-1}}, \frac{A_t}{A_{t-1}}, x_t^{(-1)}\right),$$

$$\frac{V_t}{A_{t-1}} = \max_{C_t} \left(\left(\frac{C_t}{A_{t-1}}\right)^{1-\frac{1}{\psi}} + \left(\frac{1}{A_{t-1}}\right)^{1-\frac{1}{\psi}} \beta (E_t V_{t+1}^{1-\gamma})^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right)^{\frac{1}{1-\frac{1}{\psi}}},$$

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

As compared to models with time-additive preferences the value function $\tilde{V}_t$ and the expression for the certainty equivalent $\left(E_t \tilde{V}_{t+1}^{1-\gamma}\right)^{\frac{1}{1-\gamma}}$ appear in the Euler equation and therefore have to be approximated. Other equilibrium conditions in their stationary form are:

$$E_t\left[M_{t+1}\left(1-\delta+\alpha\left(\frac{\tilde{A}_{t+1}}{\tilde{K}_{t+1}}\right)^{1-\alpha}\right)\right]=1$$

$$\tilde{C}_t+\tilde{I}_t=\tilde{A}_t^{1-\alpha}\tilde{K}_t^{\alpha},$$

$$\tilde{K}_{t+1}\tilde{A}_t=(1-\delta)\tilde{K}_t+\tilde{I}_t,$$

$$x_{t+1}=H_0+H_1x_t+H_2\epsilon_{t+1},$$

where $x_t^1=\ln\tilde{A}$ and

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

At the non-stochastic steady state:

$$\begin{aligned}
x &= (I-H_1)^{-1}H_0,\\
\tilde{A} &= \exp(x^1),\\
\tilde{K} &= \tilde{A}\left(\frac{\beta^{-1}\tilde{A}^{1/\psi}-(1-\delta)}{\alpha Z}\right)^{\dfrac{1}{\alpha-1}},\\
\tilde{I} &= (\tilde{A}-(1-\delta))\tilde{K},\\
\tilde{V} &= \left(\frac{\tilde{C}^{1-\frac{1}{\psi}}}{1-\beta\tilde{A}^{1-\frac{1}{\psi}}}\right)^{\frac{1}{1-\frac{1}{\psi}}}.
\end{aligned}$$

In addition, at the steady state, the risk-free rate and the PD ratio are:

$$R_f=\beta^{-1}\tilde{A}^{1/\psi},$$

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

D 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:

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

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

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

We expand the functions g and h around the $\sigma = 0$ and $x_t = \bar{x}$ point. For estimation purposes we approxiate 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 terms, to the second order, risk aversion matters for the difference between the stochastic steady state and the non-stochastic steady state but not the dynamics of the variables.

E Data description

This appendix describes the data used in the paper. We use data on U.S. real nondurables and services consumption per capita from the Bureau of Economic Analysis. 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. We create a proxy for the ex-ante risk-free rate by forecasting the ex-post quarterly real return on three-month Treasury bills with past one-year inflation and the most recent available three-month nominal bill yield. These series are identical to those used by Beeler and Campbell (2012) in their quarterly empirical work. See their online Appendix for further details on the data construction. Real GDP is obtained as Real Gross Domestic Product (BEA, NIPA table 1.1.6., line 1). Investment is Gross Private Domestic, Fixed Investment, Nonresidential and Residential (BEA NIPA table 1.1.5., lines 8 and 11), and deflated using the GDP deflator (BEA NIPA table 1.1.5., line 1 and BEA NIPA table 1.1.6., line 1). These series are then converted to per capita terms by dividing by the civilian non-institutionalized population aged 16 and over. In our VAR analysis of news shocks we follow the lead of Barsky and Sims (2011) and use a quarterly version of the

Basu, Fernald, and Kimball (2006) total factor productivity (TFP) series.

Table 1: Calibrated and Estimated Parameters

Panel A reports the calibrated parameters of the model. Panel B reports the parameters of the model estimated using classical maximum likelihood methods, in particular those defining the stochastic processes of anticipated and unanticipated innovations. The parameters not significantly different from 0 are not reported. Asymptotic standard errors based on the outer-product estimate of Fisher's information matrix are reported in parantheses. The reference period is one quarter.

Panel A: Calibrated Parameters

Parameter		Value
Capital share	α	0.340
Capital depreciation	δ	0.025
TFP growth (%)	μ	0.400
Subjective discount factor	β	0.998
Relative risk aversion	γ	4.278

Panel B: Estimated Parameters

Parameter		Value	s.e.
Elasticity of inter-temporal substitution	ψ	1.494	(0.643)
Leverage	λ	6.145	(0.136)
Volatility of un-anticipated TFP shocks (%)	σ^0	1.070	(0.070)
Volatility of 1-quarter anticipated TFP shock (%)	σ^1	0.690	(0.060)
Volatility of 4-quarter anticipated TFP shock (%)	σ^4	0.920	(0.060)
Persistence in TFP growth	ρ	0.381	(0.076)

Table 2: Macroeconomic and Asset Pricing Moments

Panels A and B of the Table report key macroeconomic and asset pricing moments for the estimated news model and compares them to the data and a model without news shocks. Moments are computed at quarterly frequency and annualised (except for log PD ratio) by multiplying unconditional means by 4 and standard deviations by 2. The standard RBC model is calibrated to the same preferences and technology parameter values as the news model. However, it assumes un-anticipated iid TFP growth shock only. The standard deviation of TFP surprises in the standard RBC model is calibrated to match the consumption growth volatility of the news model. Data are 1947Q2-2012Q4. GMM standard errors (three Newey-West lags) are reported in parantheses.

Panel A: Macro Moments

	Data		Estimated model	Standard RBC
$\sigma\,(\Delta c)\,\%$	1.05	(0.07)	1.41	1.40
$\sigma\,(\Delta y)\,\%$	1.99	(0.14)	2.27	2.92
$\sigma\,(\Delta i)\,\%$	4.94	(0.41)	5.76	6.10
$corr\,(\Delta c,\Delta y)$	0.49	(0.07)	0.55	0.97
$corr\,(\Delta c,\Delta i)$	0.48	(0.07)	0.16	0.94
$corr\,(\Delta y,\Delta i)$	0.65	(0.05)	0.91	0.99

Panel B: Asset Pricing Moments

	Data		Estimated model	Standard RBC
$E\,(r_f)\,\%$	0.81	(0.32)	1.56	1.61
$\sigma\,(r_f)\,\%$	1.16	(0.11)	0.36	0.30
$E\,(pd)$	3.50	(0.07)	3.50	4.37
$\sigma\,(pd)$	0.42	(0.03)	0.39	0.30
$E\,(r_d - r_f)\,\%$	6.04	(2.10)	5.37	4.17
$\sigma\,(r_d - r_f)\,\%$	16.8	(1.08)	28.3	24.9

Figure 1: Macro-finance cross-correlations

This figure reports the lead and lag cross-correlations between excess stock-market returns (top row) and log PD ratios (bottom row) with output, investment, and consumption growth implied by the news model, an otherwise identical model without news, and in the data. Stock-market returns and the growth rates of macroeconomic variables are annual. Data are 1947Q2-2012Q4. Log PD ratio in the data is adjusted for breaks. In particular we follow Lettau and VanNieuwerburgh (2008) and assume two changes in the mean in 1954 and 1994.

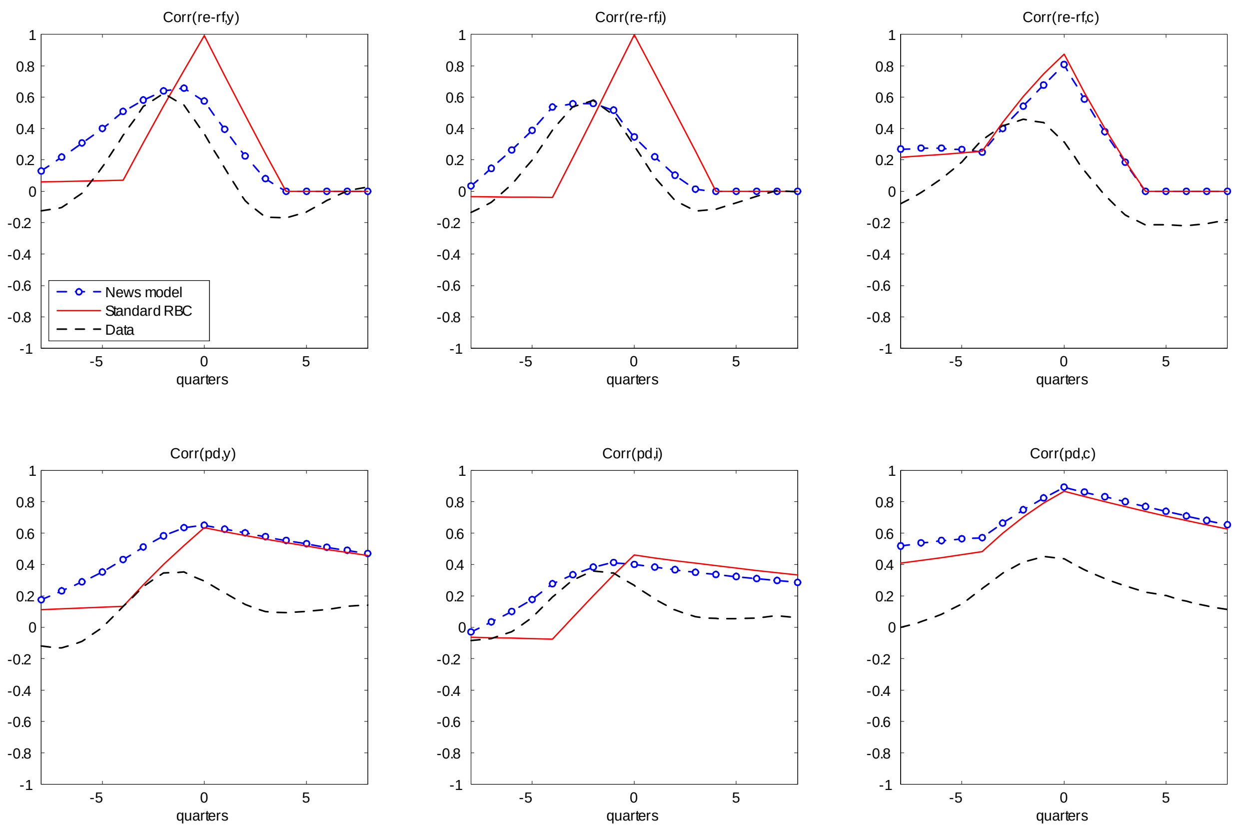

Figure 2: EIS and News Propagation

This figure illustrates the role of the EIS parameter in matching the lead of asset prices over macroeconomic quantities. It reports the lead and lag cross-correlations between log PD ratios with investment growth implied by the news model, an otherwise identical model with EIS=0.1, and in the data. Investment growth rates are annual. Data are 1947Q2-2012Q4. Log PD ratio in the data is adjusted for breaks. In particular we follow Lettau and VanNieuwerburgh (2008) and assume two changes in the mean in 1954 and 1994.

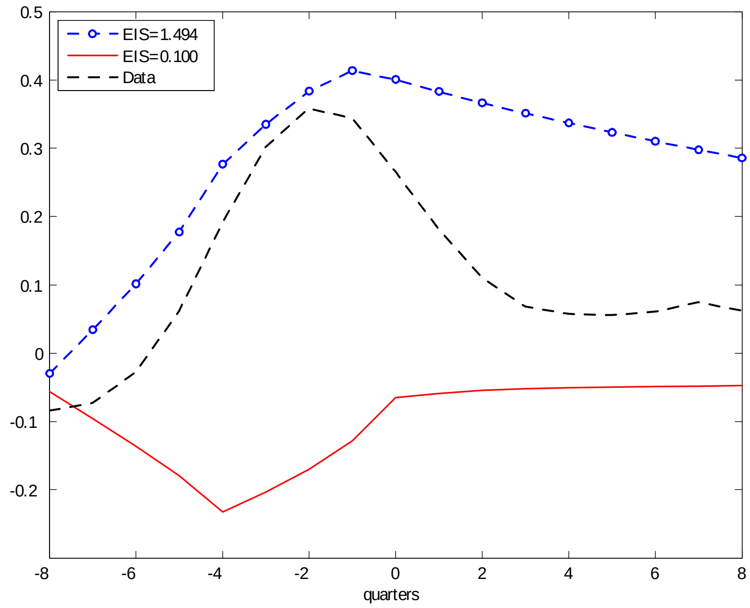

Figure 3: Test of the VAR Approach on Simulated Data

This figure illustrates the ability of the VAR approach to identify news shocks. Bars correspond to the theoretical impulse responses of the variables in the news model to a linear combination of shocks anticipated one and four quarters ahead. The solid lines and areas correspond to the responses and confidence intervals identified from the simulated data using a VAR approach.

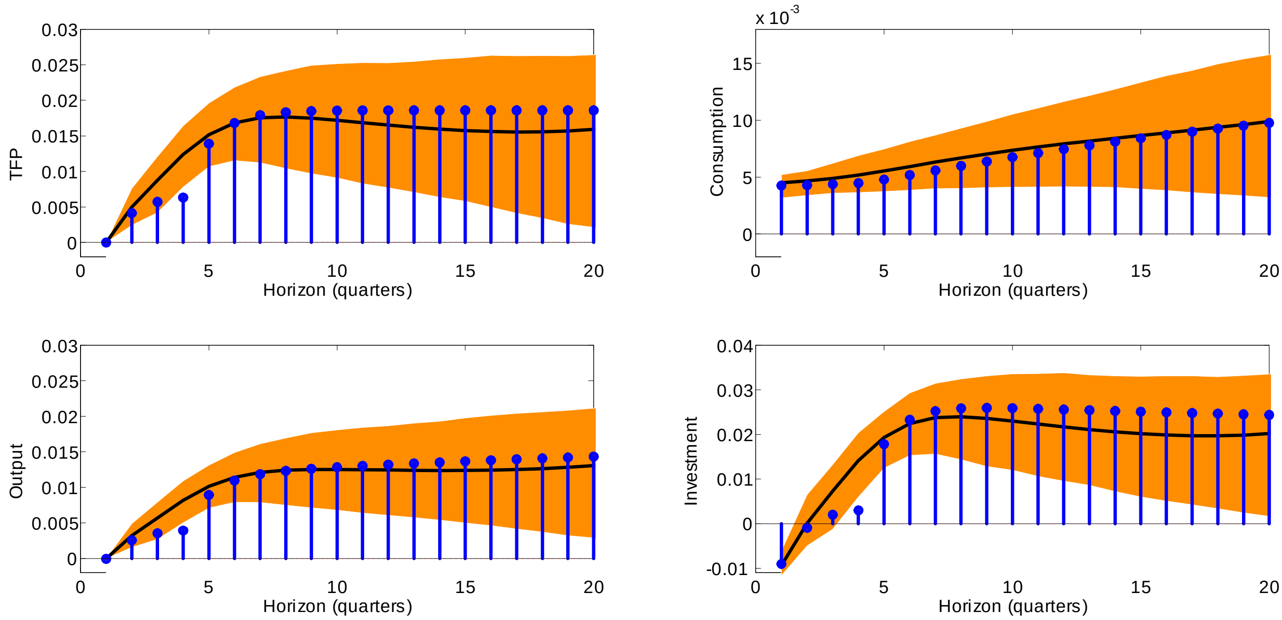

Figure 4: Loadings on Anticipated Shocks by Horizon

This figure reports the coefficients from a regression of news shocks identified using the VAR approach in the simulated data on the true underlying innovations with different anticipation horizon.

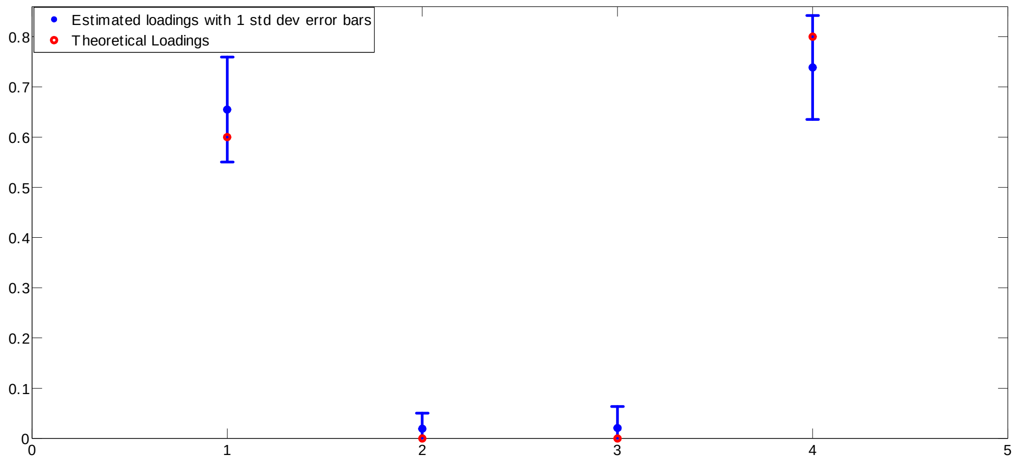

Figure 5: Impulse Responses

This figure reports the estimated impulse responses of TFP, consumption, output, and stock prices to the identified news shock and compares them to the theoretical response to a combination of shocks anticipated one and four quarters ahead. The shaded areas are the 95% confidence bands from the bias-corrected bootstrap procedure of Kilian (1998). Data are 1947Q2-2012Q4.

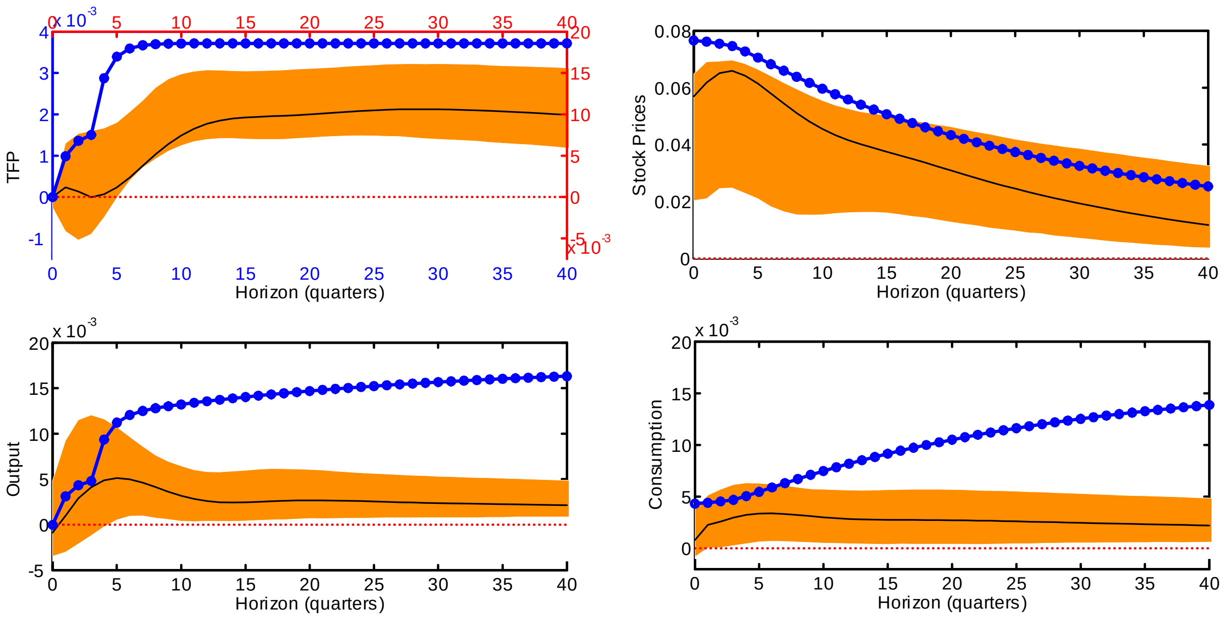

Figure 6: PD Ratio

This figure reports model's prediction for the PD ratio, together with the actual PD ratio from the S&P500 index. The model output is produced by feeding it with the VAR-identified news and surprise shocks. Panel A reports actual S&P500 PD ratio. In Panel B the PD ratio is adjusted for shifts in the long-run mean. In particular we follow Lettau and VanNieuwerburgh (2008) and assume two changes in the mean in 1954 and 1994. Data are 1947Q2-2012Q4.