News, Beliefs, and Aggregate Risk

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Abstract

We infer agents' expectations about future fundamentals using a New-Keynesian general equilibrium model augmented with expectation, or news, shocks. Accounting for agents' expectations at the business cycle horizon results in aggregate risk factor innovations that have significant explanatory power for the cross-section of stock and bond returns. Further, disentangling the correctly anticipated changes in fundamentals from the variation in beliefs that ultimately do not realize, we find that the pure belief component of news is important to explain the value premium. In contrast, exposure to correctly anticipated changes in future fundamentals is important for long-term bonds and cash-flow duration portfolios.

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1 Introduction

The view that economic fluctuations are driven by agents' expectations has a long history.[1] In the expectation-driven business cycle paradigm, agents respond to changes in their expectations about the future economic fundamentals that cannot be trivially identified by the econometrician from the history of these fundamentals.[2]

In this paper, we show the importance of agents' latent information about the forces driving the business cycle for our understanding of aggregate risk. First, we infer agents' expectations at the business cycle horizon using a dynamic stochastic general equilibrium model. Second, we incorporate agents' information into cross-sectional asset pricing tests. In particular, we find that innovations to aggregate consumption measured conditional on agents' information have significant explanatory power for equity value and duration, as well as bond portfolios – test assets that continue to challenge the asset pricing theory.

To study agents' expectations, we use a standard New-Keynesian model and augment it with productivity news shocks; i.e., changes in productivity that agents anticipate at different horizons. By definition, news are information available to agents not yet reflected in the production possibilities of the economy. This makes their identification not trivial. We use both the joint dynamics of multiple endogenous variables and the theoretical restrictions imposed by the structural model to overcome this challenge. The model has an equivalent representation in which agents receive noisy signals about future productivity, providing us with additional intuition for the results and allowing us to disentangle the effect of correctly anticipated changes in future fundamentals from the effect of variation in pure beliefs about the future.[3]

The model matches salient macroeconomic and asset pricing moments. Importantly, our estimates reveal the important role of news. The magnitude of one-quarter and four-quarter news shocks is similar to productivity growth surprises. Moreover, shocks anticipated eight

[1] See Pigou (1927) for an early exposition of this view and the literature on news shocks pioneered by the work of Beaudry and Portier (2004).

[2] See Cochrane (1994) on the role of the information available to the agents but not to the econometrician.

[3] The literature has often distinguished between news and noise; see, for instance, Lorenzoni (2011) and Barsky and Sims (2012). Chahrour and Jurado (2018) show that the two information structures, "news" and "noise", are observationally equivalent when innovations are normally distributed.

quarters ahead remain statistically and economically significant. Combined across all horizons, news about future productivity explain an important fraction of macroeconomic and asset price volatility. Finally, we find that macroeconomic fluctuations are primarily driven by correctly anticipated changes in future fundamentals. Compared to macroeconomic fluctuations, asset price movements are to a larger degree due to variation in pure beliefs.

Having estimated agents' expectations and established their importance for macro-finance fluctuations, we consider their role for risk premia. The novelty of our analysis lies in conditioning innovations in risk factors on investors' information or, equivalently, in the identification of news about future fundamentals that represent the true innovations to the agents' information set, in line with the discussion in Cochrane (1994, 2005). At the same time, our analysis is not specific to one particular type of preferences: alongside more general recursive preferences, we focus on the time-additive utility case where innovations to consumption represent the relevant measure of aggregate risk. Our findings are striking: once we account for agents' expectations, innovations to consumption explain a large fraction of the cross-sectional differences in the expected returns of the 25 Fama–French size and book-to-market portfolios. This finding contrasts with the poor results obtained when we use realized consumption growth, market portfolio returns, or a combination of these two variables as risk factors. Furthermore, innovations conditional on agents' information perform well for stock portfolios sorted on firm cash flow duration – see Weber (2018) – and for the long-term bonds. Finally, we find that news shocks at both short and longer horizons are important for explaining the cross section of asset returns.

Our explanation for the value premium is consistent with the recent findings in Golubov and Konstantinidi (2019): we find that the association between book-to-market and consumption innovation (or, alternatively, recursive discount factor innovations) is driven by the market-to-value component, which is shown by the authors to explain all of the value strategy return, and not by the value-to-book component.[4] Interestingly, exposure to the pure belief component of news is important to account for the role of the market-to-value in explaining the value premium. In contrast, exposure to correctly anticipated changes in future fundamentals is im-

[4]We thank Andrey Golubov for generously sharing the book-to-market components data.

portant for long-term bonds and cash flow duration portfolios.

Our modeling choice of introducing news in total factor productivity is guided by a large empirical literature showing that these shocks are important sources of business cycle fluctuations in the postwar United States. For instance, Barsky and Sims (2012) show that news shocks about future productivity account for a significant fraction of the innovation in measured confidence and economic activity. More recently, Barsky, Basu and Lee (2015) use a host of reduced–form vector auto-regressive (VAR) specifications to exhaustively document that news shocks in total factor productivity exist and are quantitatively important for business cycle fluctuations.

Our paper is related to the long-run risk literature dating back to Bansal and Yaron (2004). This literature shows that the innovations to the persistent component of consumption growth – empirically documented in Schorfheide et al. (2018) and commonly referred to as a long-run risk shocks – command a significant risk premium under recursive preferences, providing a potential resolution of the equity premium puzzle. The long-run risk mechanism has also proved useful to explain the cross section of expected stock returns; see, for instance, Bansal, Dittmar and Lundblad (2005), Boguth and Kuehn (2013), and Croce et al. (2017). Despite a similar emphasis on agents' expectations, our results differ from those documented in the long-run risk literature in two important ways pertaining to the dynamics of fundamentals and the role of preferences. First, shifting the focus from the persistence properties of productivity and consumption series to latent information that cannot be inferred from the univariate series themselves allows us to identify large changes in agents' expectations at the business cycle horizon. Thus, our results are complementary to the long-run risk literature, as they shed light on a different component of agents' expectations. Second, we show that recursive preferences do not play a particular role for our results, unlike in long-run risk models.

Our paper is also related to the growing production-based asset pricing literature. See Kaltenbrunner and Lochstoer (2010), Gourio (2012), Croce (2014), and Kung and Schmid (2015) to mention just a few contributions. A strand in this literature studies nominal bond risk premia in New-Keynesian models; see, for instance, Rudebusch and Swanson (2012), Li and Palomino (2014), and Kung (2015). In addition, Ai et al. (2013), Belo et al. (2014), and Weber (2017), among others, explore the implications of different types of firm heterogeneity in macro-finance models for the cross section of stock returns. Relative to these papers, we do not introduce additional frictions or a novel type of preferences; instead, we augment a standard New-Keynesian model with a rich information structure, and use this framework to estimate the changes in agents' expectations, which we show to have an important role for the measurement of the aggregate macroeconomic risk.

Our study adds to a growing literature that seeks to improve the empirical performance of the consumption-based capital asset pricing model by redefining the relevant measure of consumption; see Ait-Sahalia et al. (2004), Yogo (2006), Malloy et al. (2009), Savov (2011), Kroencke (2017), and Belo et al. (2019).[5] Differently from these papers, we use the canonical measure of consumption based on the National Income and Product Accounts (NIPA), and instead identify innovations in this consumption measure conditional on agents' information. Our work is also related to Jagannathan and Wang (2007), Parker (2003) and Parker and Julliard (2005), and Bryzgalova and Julliard (2018), who propose measuring consumption risk as consumption growth realized over several subsequent quarters. We provide a theoretical interpretation of these long–horizon consumption measures as proxies for anticipated changes in productivity. Importantly, the asset pricing performance of our model-implied consumption risk factor is not subsumed by the ultimate consumption factor of Parker and Julliard (2005). In fact, we find that in a two-factor setting that includes the ultimate consumption along with our consumption risk factor, the price of risk of ultimate consumption turns insignificant, whereas the price of risk of our consumption risk factor continues to stay significant.

Finally, our paper relates to Beaudry and Portier (2006) and Kurmann and Otrok (2013), who show that stock prices and the slope of the term structure of nominal interest rates are, respectively, informative about news shocks. In addition, Barsky, Basu and Lee (2015) cite the deflationary impact of a news shock as one of the most robust features of the data. We jointly consider all the above variables — inflation, aggregate stock prices, and term structure

[5] Specifically, Savov (2011) proposes to measure consumption using garbage; Kroencke (2017) suggests to "unfilter" NIPA consumption; Ait-Sahalia et al. (2004) and Yogo (2006) study the role of luxury and durable goods, respectively; Malloy et al. (2009) use stockholder consumption; and Belo et al. (2019) suggest to use non–pecuniary drivers of utility that are left out of, and yet affect, aggregate consumption.

slope — alongside other macroeconomic aggregates in our identification of news. To faciliate this exercise, differently from these authors, we use a dynamic stochastic general equilibrium (DSGE) model rather than a VAR. Our analysis of news shocks through the lens of a DSGE model follows the lead of Schmitt-Grohe and Uribe (2012), Barsky and Sims (2012), Blanchard, L'Huillier and Lorenzoni (2013), Avdjiev (2016), and Forni, Gambetti, Lippi and Sala (2017). Similarly, our paper is related to the strand of literature which argues for using DSGE models for forecasting; see, for instance, Del Negro and Schorfheide (2013).

The rest of this paper is structured as follows. Section 2 introduces our estimation strategy and discusses the estimation results. Section 3 incorporate our estimates of agents' expectations into cross-sectional asset pricing tests. Section 4 concludes.

2 Shocks

2.1 Agents' Information

Motivated by the evidence on news-driven business cycles, we allow agents to form their expectations about the economic fundamentals based on a rich information set $\mathcal{I}_t$ described below. In our model, these underlying economic fundamentals have the interpretation of the total factor productivity. In particular, we specify productivity growth $\Delta \ln A_t$ as autoregressive and subject to anticipated and unanticipated innovations:

$$\Delta \ln A_t = (1-\rho)\mu + \rho \Delta \ln A_{t-1} + \varepsilon_{0,t} + \varepsilon_{1,t-1} + \varepsilon_{4,t-4} + \varepsilon_{8,t-8}, \tag{1}$$

where $\varepsilon_{0,t}$ are date t productivity surprises, while innovations $\varepsilon_{j,t-j}$ are anticipated j periods ahead: they affect date-t productivity, but are period $t-j$ information. Anticipated *permanent* changes in productivity are in line with the empirical evidence on productivity news shocks; see, for instance, Barsky et al. (2015). We borrow the specification in (1) from Schmitt-Grohe and Uribe (2012) who show the importance of shocks anticipated at different horizons.[6] Equa-

[6]We also consider additional shocks anticipated twelve and sixteen periods ahead. Empirically, we find that twelve- and sixteen-quarter news do not play a significant role. Moreover, modelling sixteen quarter news consid-

tion (1) is a short notation for a state-space representation with 8 latent variables tracking agents' expectations about future fundamentals up to 8 quarters ahead, see Appendix A.1.

Under independent and jointly normal shocks, the information structure described by (1) is observationally equivalent to a setting where agents receive noisy signals about the realization of future productivity and, upon receiving each signal, update their beliefs rationally, as shown in Chahrour and Jurado (2018).[7] This equivalent information structure can be formally represented as

$$\Delta \ln A_t = (1-\rho)\mu + \rho \Delta \ln A_{t-1} + \xi_t, \tag{2}$$

$$s_{1,t-1} = \xi_t + \nu_{1,t-1}, \tag{3}$$

$$s_{4,t-4} = \xi_t + \nu_{4,t-4}, \tag{4}$$

$$s_{8,t-8} = \xi_t + \nu_{8,t-8}, \tag{5}$$

where $\nu_{j,t-j}$ is the noise component of the signal $s_{j,t-j}$ received j periods ahead of the realization of the productivity shock ξ_t.[8] In other words, agents receive signals at $t-8$, $t-4$ and $t-1$, and sequentially update their beliefs about the realization of ξ_t at t proportionally to each signal's Kalman gain. Appendix A.1 shows how shocks in (2)-(5) can be written in terms of shocks in (1).

The equivalent representation highlights the noisy character of agents' information in (1) as news anticipated at longer horizons may be offset by shorter-horizon news before having any effect on realized productivity. The noise shocks $\nu_{j,t-j}$ capture the variation in agents' pure beliefs. Thus, the equivalent representation of agents's information allows us to disentangle the correctly anticipated changes in fundamentals from the variation in beliefs that ultimately do not realize.

Given the observed path of the economy, allowing for a richer information set $\mathcal{I}_t$ leads to a more accurate decomposition of the representative investor's (log) stochastic discount factor

erably increase the number of state variables that track agents' expectations and are computationally challenging.

[7] Song and Tang (2018) consider the additional effects that arise when innovations are not normally distributed.

[8] Note that the agents learn about the realization of the shocks, not model parameters, which are known to them. In this sense, our model differs from models with parameter learning as, for instance, in Collin-Dufresne, Johannes and Lochstoer (2016).

$m_{t,t+1}$ into the expected component $\mathrm{E}\left[m_{t,t+1} \mid \mathcal{I}_t\right]$ and the innovation $m_{t,t+1} - \mathrm{E}\left[m_{t,t+1} \mid \mathcal{I}_t\right]$ or, equivalently, to the identification of shocks that represent the true innovations to the agents' information set. The asset pricing factor that takes into account agents' information $\mathcal{I}_t$ can thus be written as

$$m_{t,t+1} - \mathrm{E}\left[m_{t,t+1} \mid \mathcal{I}_t\right] \approx m_\varepsilon' \varepsilon_{t+1}, \tag{6}$$

where ε_t is the vector of all the fundamental shocks buffeting the economy and m_ε is a vector of coefficients determined by the economy's response to these fundamental shocks.

Alongside a specification for $m_{t,t+1}$ based on recursive utility which is discussed below, we also focus on the special case where the innovation to realized consumption is the relevant risk factor

$$c_{t+1} - \mathrm{E}\left[c_{t+1} \mid \mathcal{I}_t\right] \approx c_\varepsilon' \varepsilon_{t+1}. \tag{7}$$

This case makes the role of conditional information more explicit. First, consumption innovations can be compared to the observed consumption growth $c_{t+1} - c_t$. For these two factors to have different properties, there has to be a large variation in expected consumption growth at the short horizon. Identifying this variation in agents' expectations is at the heart of our analysis. Second, this case illustrates our difference with the long-run risk models in which small innovations in expected consumption $\mathrm{E}\left[c_{t+k} \mid \mathcal{I}_{t+1}\right] - \mathrm{E}\left[c_{t+k} \mid \mathcal{I}_t\right]$ for long horizons k are the main source of the priced risk independent from the realized consumption risk. Using (7) as a measure of aggregate risk, we show that our results do not rely on a particular type of preferences under which expected consumption innovations are priced.

2.2 Estimation Methodology

To construct the asset pricing factors outlined in (6) and (7), we use a dynamic stochastic general equilibrium (DSGE) model. Our choice is motivated by several reasons. First, note that the latent information generated by (1) cannot be identified by the econometrician from the time series of the productivity itself.[9] Second, the model imposes theoretical restrictions,

[9]This is in contrast to, for instance, Croce (2014), who fits a time series model to the productivity series to identify a small persistent component in productivity growth.

which facilitate the estimation when agents' information set is described by multiple latent state variables; see, for instance, Schmitt-Grohe and Uribe (2012). Recall that in our case eight latent state variables track the term structure of agents' expectations about future fundamentals up to eight quarters ahead. See also Del Negro and Schorfheide (2013) who argue for using DSGE models for forecasting. Finally, in addition to estimating the expectations in (6) and (7), a model allows us to identify the structural shocks ε_t and measure their contribution to the aggregate risk.[10]

Next, we present our model and discuss the solution and estimation methodology.

Macroeconomic model. Our model is a version of the standard New-Keynesian framework. We opt for the most parsimonious model that matches the moments of interest.

The representative household owns the capital stock, K_t, and the claim to firms' profits, Θ_t; she chooses consumption C_t, labor L_t, and investment in capital I_t to maximize her lifetime utility U_t defined recursively[11,12]

$$U_t = \frac{C_t^{1-1/\psi}}{1-\frac{1}{\psi}} - \eta_0 \frac{A_t^{1-1/\psi} L_t^{1+1/\eta}}{1+\frac{1}{\eta}} + \beta \left[\mathrm{E}_t \left[U_{t+1}^{\gamma} \right] \right]^{\frac{1}{\gamma}}, \tag{8}$$

subject to:

$$\begin{aligned} C_t + I_t &= W_t L_t + R_{K,t} K_t + \Theta_t, \\ K_{t+1} &= \left[1 - \delta + \zeta_1 \left(\frac{I_t}{K_t} \right)^{\zeta} + \zeta_2 \right] K_t, \qquad (9) \\ W_t - W_{F,t}^{1-\rho_w} W_{t-1}^{\rho_w} &= 0. \qquad (10) \end{aligned}$$

In the preferences specified by (8), β is the time discounting rate, ψ is the elasticity of inter-

[10] As discussed above, the presence of anticipated innovations with multi-period anticipation horizons introduces multiple latent state variables. This proliferation of states makes the VAR invertibility problem more likely (see, e.g. Lippi and Reichlin, 1994; Leeper et al., 2013; Beaudry and Portier, 2014). Thus, we follow the lead of Schmitt-Grohe and Uribe (2012) and Blanchard et al. (2013) who show that a structural estimation based on a DSGE model does not suffer from the aforementioned invertibility problem. See also Section 4.2.3 in Beaudry and Portier (2014) for a discussion of invertibility issues due to signal-extraction problem.

[11] Here we assume $\frac{C_t^{1-1/\psi}}{1-\frac{1}{\psi}} - \eta_0 \frac{A_t^{1-1/\psi} L_t^{1+1/\eta}}{1+\frac{1}{\eta}} > 0$. The opposite case is treated symmetrically; see Swanson (2012).

[12] The productivity term in the utility function ensures a balanced growth path and can be microfounded by a model in which households receive utility from both market goods and home production; see, for instance, Campbell and Ludvigson (2001) and Rudebusch and Swanson (2012).

temporal substitution (EIS), and η is the Frisch elasticity. Adjusting for the labor margin following Swanson (2012), the effective relative risk aversion is approximately equal to RRA $\approx (\psi+\eta)^{-1} + (1-\gamma)\left(\frac{1}{1-1/\psi} - \frac{1}{1+1/\eta}\right)^{-1}$. The case $\gamma = 1$ corresponds to time-additive utility. The real stochastic discount factor $M_{t,t+1}$ implied by household's preferences (8) is given by

$$M_{t,t+1} = \beta \left[\frac{V_{t+1}}{\mathrm{E}_t\left[V_{t+1}^{\gamma}\right]} \right]^{\gamma-1} \left[\frac{C_{t+1}}{C_t} \right]^{-1/\psi}, \tag{11}$$

where V_t is the value function associated with household's optimization. Capital accumulation in (9) is subject to adjustment costs that depend on ζ. Real wages are subject to inertia captured by (10), where $W_{F,t}$ is the wage determined by the Frisch labor supply relationship $W_{F,t} = \eta_0 A_t^{1-1/\psi} L_t^{1/\eta} C_t^{1/\psi}$.

There is a continuum of monopolistically competitive firms indexed by $j \in [0,1]$. Every period each firm with probability $1-\theta$ has the opportunity to adjust its output price $P_{o,t}(j)$ to maximize

$$\mathrm{E}_t \left[\sum_{s=0}^{\infty} \theta^s M_{\$,t,t+s} \left[P_{o,t}(j) Y_{t+s}(j) - P_{t+s} \left[W_{t+s} N_{t+s}(j) + R_{K,t+s} K_{t+s}(j) \right] \right] \right] \tag{12}$$

subject to

$$Y_{t+s}(j) = Z_{t+s} K_{t+s}(j)^{\alpha} \left(A_{t+s} N_{t+s}(j)\right)^{1-\alpha}, \tag{13}$$

$$Y_{t+s}(j) = \left[\frac{P_{o,t}(j)}{P_{t+s}} \right]^{-\varepsilon} Y_{t+s}, \tag{14}$$

where the aggregate price index P_t is given by

$$P_t = \left[\int_0^1 P_t(j)^{1-\varepsilon} dj \right]^{\frac{1}{1-\varepsilon}} = \left[(1-\theta) P_{o,t}^{1-\varepsilon} + \theta P_{t-1}^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}. \tag{15}$$

The expression in (12) represents the expected profits during the time period in which firm j will not be able to adjust its price discounted using household's stochastic discount factor $M_{\$,t,t+s}$. The within-period profits are the difference between the revenue $P_{o,t}(j) Y_t(j)$ and the remuneration of hired labor $N_t(j)$ and capital $K_t(j)$ at real wage W_t and capital return rate $R_{K,t}$, respectively. The firms have identical production technology (13) that depends on permanent productivity shocks through A_t and transitory productivity shocks through Z_t, where

$$\ln Z_t = \rho_z \ln Z_{t-1} + \varepsilon_{z,t}. \tag{16}$$

The demand functions for firms' output is given by (14), where ε determines the mark-up charged by the firms.

The monetary authority sets the one period (gross) nominal interest rate $R_{n,t}$ using a modified Taylor rule

$$R_{n,t} = R_{n,t-1}^{\rho_{rn}} \left[R_n \left[\frac{\Pi_t}{\Pi} \right]^{\phi_\pi} \left[\frac{Y_t/A_t}{Y/A} \right]^{\phi_{y1}} \left[\frac{Y_t/Y_{t-1}}{Y/Y_{-1}} \right]^{\phi_{y2}} \right]^{1-\rho_{rn}} e^{\varepsilon_{m,t}}, \tag{17}$$

where $\Pi_t = P_t/P_{t-1}$ is the gross inflation rate, R_n, Π, Y/A and Y/Y_{-1} are steady state values of the corresponding variables, and $\varepsilon_{m,t}$ is a monetary policy shock. Adding to the standard Taylor rule, Eq. (17) allows for the monetary authority's response to output growth, a variable that is more readily observed in practice than the output gap. The rule also assumes interest rate smoothing, which is generally acknowledged to be a realistic feature of monetary policy making.

Markets are complete. We focus on two types of securities: default-free nominal zero-coupon bonds as model counterparts of Treasury securities and, following a common approach in the finance literature, the levered consumption claim as the model counterpart of the aggregate stock market.[13] Specifically, we assume that the growth in the dividends paid by the levered consumption claim relative to the TFP trend is equal to consumption growth relative to the same trend amplified by the leverage parameter χ:

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

[13] See, for instance, Bansal and Yaron (2004) and Kaltenbrunner and Lochstoer (2010). This approach 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.

We assume all the innovations $\varepsilon_{0,t}$, $\varepsilon_{1,t}$, $\varepsilon_{4,t}$, $\varepsilon_{8,t}$, $\varepsilon_{z,t}$, and $\varepsilon_{m,t}$ to be independent and normally distributed. Together with the exogenously given Eqs. (1), (9), (10), (16)-(17), equilibrium is characterized by the set of conditions presented in Appendix A.1.

Solution. We solve the model using a second-order approximation of the policy functions that characterize the equilibrium dynamics, see Schmitt-Grohe and Uribe (2004). Employing at least a second-order approximation is crucial to match financial moments in the data by capturing non-zero average risk premia in equities and Treasury bonds. To ensure stable sample paths and the existence of finite unconditional moments, we adopt the pruned state-space system for non-linear models suggested by Andreasen, Fernández-Villaverde and Rubio-Ramírez (2017). Intuitively, pruning means omitting terms of higher-order than the considered approximation order when the system is iterated forward in time.[14] We then follow Andreasen et al. (2017) and derive closed-form solutions for the unconditional first and second moments of the pruned state-space of the model which allows us to estimate model parameters using a simple GMM routine as discussed below.

Estimation. We calibrate a range of deep model parameters and estimate the rest of the parameters, including the standard deviations of all the structural shocks; see also Section 2.3. In the estimation we use the following macroeconomic and financial time series for the sample from 1970:Q1 to 2016:Q4: log output growth, Δy_t; log consumption growth, Δc_t; log investment growth, Δi_t; one-quarter inflation, Π_t; the one-quarter nominal interest rate, $y_t^{(1)}$; the slope of the term structure, $y_t^{(40)} - y_t^{(1)}$; and the log price-to-dividend ratio, pd_t. Further details about the data are deferred to Appendix A.2. The GMM estimation relies on the mean, the variance, the contemporaneous covariances and the first auto- and cross-covariances in the

[14] We verify that pruning does not drive our results by simulating the model at higher-order without pruning. In particular, the results do not change even when we use a fifth-order approximations.

data as moments.[15] Hence, we let

$$q_t = \begin{bmatrix} \mathbf{data}_t \\ diag\left(\mathbf{data}_t \mathbf{data}_t'\right) \\ vech\left(\mathbf{data}_t \mathbf{data}_t'\right) \\ diag\left(\mathbf{data}_t \mathbf{data}_{t-1}'\right) \\ vech\left(\mathbf{data}_t \mathbf{data}_{t-1}'\right) \end{bmatrix}.$$

Letting $\boldsymbol{\theta}$ contain the structural parameters, our GMM estimator is given by

$$\boldsymbol{\theta}_{GMM} = \text{argmin}_{\boldsymbol{\theta}\in\boldsymbol{\Theta}} \left(\frac{1}{T}\sum_{t=1}^{T} \boldsymbol{q}_t - m(\boldsymbol{\theta})\right)' \boldsymbol{W} \left(\frac{1}{T}\sum_{t=1}^{T} \boldsymbol{q}_t - m(\boldsymbol{\theta})\right) \tag{18}$$

Here, W is a positive definite weighting matrix and $m(\boldsymbol{\theta})$ is a vector that contains the model-implied unconditional moments computed in closed-form. We use the conventional two-step implementation of GMM by letting $\boldsymbol{W}_T = \text{diag}\left(\hat{\boldsymbol{S}}^{-1}\right)$ in a preliminary first step to obtain $\hat{\boldsymbol{\theta}}^{\text{step 1}}$ where $\hat{\boldsymbol{S}}$ denotes the long-run variance of $\frac{1}{T}\sum_{t=1}^{T}\boldsymbol{q}_t$ when re-centered around its sample mean. Our final estimates $\hat{\boldsymbol{\theta}}^{\text{step 2}}$ are obtained using the optimal weighting matrix $\boldsymbol{W}_T = \hat{\boldsymbol{S}}^{-1}_{\hat{\boldsymbol{\theta}}^{\text{step 1}}}$, where $\hat{\boldsymbol{S}}_{\hat{\boldsymbol{\theta}}^{\text{step 1}}}$ denotes the long-run variance of our moments re-centered around $m\left(\hat{\boldsymbol{\theta}}^{\text{step 1}}\right)$. The long-run variances in both steps are estimated by the Newey-West estimator using 10 lags, but our results are robust to using more lags.

To summarize, the estimation procedure implemented by GMM is as follows:

- 1. Step: Let $\boldsymbol{W}_T = \text{diag}\left(\hat{\boldsymbol{S}}^{-1}\right)$ and obtain $\hat{\boldsymbol{\theta}}^{\text{step 1}}$ from (18).
- 2. Step: Use $\hat{\boldsymbol{\theta}}^{\text{step 1}}$ to compute $\boldsymbol{W}_T = \hat{\boldsymbol{S}}^{-1}_{\hat{\boldsymbol{\theta}}^{\text{step 1}}}$, and obtain $\hat{\boldsymbol{\theta}}^{\text{step 2}}$ from (18).

Structural shocks. In a next step, we use the model solution together with the estimated parameters to filter structural shocks from observed data. To do so, we have to fix the number and identity of observed variables. Our benchmark specification relies on the following five observables: real GDP, quarterly inflation, the nominal 1-quarter and 10-year Treasury yields,

[15] We also consider additional higher-order auto-covariances and find that estimation results are not affected. Indeed, as discussed below, the model simulated using our baseline parameter estimates matches well the longer-horizon auto-correlations of the variables. We thank Ian Dew-Becker for this observation.

and the real aggregate stock market return. We note that we do not use the information from the cross-section of stock or bond returns. Importantly, our results are robust to changes in the number and identity of observables as well as length of the sample period.

We use the particle filter with a swarm of 10,000 particles to extract structural shocks from our model that is approximated to the second-order. Further, we account for imprecise measurement of the observed time series by introducing measurement error that is equal to 20% of the variation in the data. Finally, we can use the resulting sets of structural shocks to iteratively simulate our model and calculate the median of these simulated paths for any variable of interest.

2.3 Estimation Results

Tables 1 and Table 2 report the calibrated and estimated parameters, and the unconditional moments generated by the model. Figure 1 displays the correlogram of the observable variables in the model and the data. See Appendix A.3 for additional discussion. Overall, the model matches well both the macroeconomic and the financial moments, including higher-order autocorrelations of the variables and moments not targeted in the estimation. We note that the parameter γ which controls the representative agent's risk aversion has no significant effect on the dynamics of macroeconomic variables, even at higher orders; see also Tallarini (2000). As such, γ is pinned down by the unconditional means of the price-to-dividend ratio, the equity risk premium, or the slope of the term structure. While the model is able to match the equity risk premium with a rather low risk aversion of 11, matching the slope of the term structure results in a value for γ implying a relative risk aversion coefficient of approximately 45. Hence, it is predominantly the average slope of the term structure which drives up the risk aversion coefficient.[16]

[Insert Tables 1 and 2 and Figure 1 about here]

In the rest of this section we focus on the variation in agent's expectations implied by the

[16] Andreasen and Jorgensen (2018) argue that the effective risk aversion is lower if one additionally takes into account the agents attitude towards the timing of risk.

model.

First, we look at the magnitude of expectation, or news, shocks. As reported in Table 1, we find that the standard deviation of one-quarter productivity news is as high as the standard deviation of productivity growth surprises, at approximately 0.5% per quarter. Moreover, we find that shocks anticipated four quarters ahead are similarly large. As the anticipation horizon increases further, the magnitude of news shocks starts decreasing, with the standard deviation of news anticipated eight quarters ahead equal to 0.2%. Note that in addition to anticipated and un-anticipated permanent productivity shocks, we also allow for transitory productivity shocks and monetary policy shocks, as is standard in the New-Keynesian models. We let the different types of shocks compete in the estimation, preventing us from mistakenly attributing a larger importance to news.

Second, we look at the contribution of news shocks to the dynamics of macroeconomic and financial variables. Panel A of Table 3 shows the contribution of the different structural shocks to the variance of endogenous variables. Our estimates reveal the considerable role of permanent productivity shocks, in particular, for the dynamics of macroeconomic aggregates and stock market returns. Panel B of the Table decomposes the variance induced by the permanent productivity shocks along two dimensions: (i) into surprises and news and (ii) into correctly anticipated (fundamental) and pure belief components as in Chahrour and Jurado (2018). Both for macroeconomic variables and for asset prices news are more important than surprises. In fact, news explain between 57 and 81 percent of the variation across the variables.[17] In contrast, an interesting separation between macroeconomic variables and asset prices emerges with respect to the fundamental and pure belief components. The pure belief component explains at most 15 percent of the variation in macroeconomic quantities. For asset prices, pure beliefs are instead more important. In particular, the belief component of news explains roughly two thirds of the variability in equity returns and about one third of the variability in the nominal short rate and the slope of the nominal term structure. Overall, our estimates attribute an important role to news shocks, and to each of the two components representing the correctly anticipated

[17] The contribution of news to the overall output volatility agrees with Crouzet and Oh (2016) who estimate it to be up to 20%.

changes in future fundamentals and the pure variation in agents' beliefs.

[Insert Table 3 about here]

Next, we present the model-implied impulse responses to a news shock and compare them to those implied by vector autoregressions (VARs). The literature proposed several different ways to identify news shocks in VARs, highlighting the advantages of our structural estimation that makes use of the theoretical restrictions imposed by an equilibrium model. We follow Barsky and Sims (2011) and Kurmann and Otrok (2013), and, as an alternative, Kurmann and Sims (2017). Since these VARs do not distinguish between news at different horizons, we present the model-implied response to the volatility-weighted average of the responses to one-, four- and eight quarters news shocks. We provide details about the data and the identification in the VARs in Appendix A.4, and details about the construction of model-implied impulse responses in Appendix A.5.

[Insert Figures 2 and 3 about here]

Figures 2 and 3 show that, in line with the intuition, the GDP, consumption, and investment respond with some delay to an anticipated increase in productivity, rising gradually to a new permanent level. Further, the realization of news shocks is characterized by the distinctive responses of inflation, aggregate price-to-dividend ratio, and term structure slope, in line with the previously documented facts.[18] First, inflation and short-term interest rates drop markedly on impact before slowly returning to their initial values. Second, positive news lead to a large increase in the aggregate price-to-dividend ratio which returns to its initial value after about two years. Finally, the slope of the term structure of interest rates increases on impact. Note that the model and the VARs agree on the sign and the magnitude of these responses.[19] Taken together, the results above help validate our identification of news shocks.[20]

[18]See Christiano et al. (2010) and Barsky, Basu and Lee (2015) on the deflationary effect of positive news shocks; Beaudry and Portier (2006) on news and stock prices; Kurmann and Otrok (2013) and Kurmann and Otrok (2017) on the strong relationship between news shocks and the slope of the term structure of interest rates.

[19]While the responses of the variables to TFP news are very similar in both VAR identifications, they disagree on the TFP response itself. The bottom right panel of Figure 2 shows that the data response of adjusted TFP is delayed and remains insignificant for almost ten quarters, a result consistent with the analysis in Kurmann and Otrok (2017). The model response is closer to Kurmann and Sims (2017) in Figure 3.

[20]See Appendix A.6 for some additional discussion on the identification of news shocks in the model.

The impulse responses in Figures 2 and 3 provide a preview of consumption predictability implied by our estimates. We now explore consumption predictability in more detail. While our main results in the next section pertain to the cross section of asset prices, the time series performance of the model provides an additional validation of our approach. Panel A of Figure 4 plots the series of the realized consumption growth and our estimate of consumption innovations. Panel B of Figure 4 plots the difference between these two series, equal to our estimate of expected consumption growth, together with the University of Michigan Index of Consumer Expectations.[21] Interestingly, we observe that these two series are closely aligned, supporting our premise that the difference between consumption growth and consumption innovations reflects agents' expectations.

[Insert Figure 4 about here]

Finally, Panel A of Figure 5 explores one particular aspect of consumption predictability, namely the predictability of consumption growth by the aggregate stock market. The figure plots the covariance of the aggregate market returns r^e_{t+1} with subsequent consumption growth $c_{t+1+h} - c_t$ for horizons h up to 24 quarters ahead. In the data, the covariance is positive for $h = 0$ and is increasing substantially up to $h = 7$ quarters. Beyond that, it plateaus and its confidence bands become larger. This pattern in the data is well replicated by the model.

[Insert Figure 5 about here]

3 Cross-section of asset returns

In this section we examine the ability of innovations in the recursive stochastic discount factor resulting from our estimation to measure aggregate risk and to explain the cross-section of asset returns. Specifically, we test

$$\mathrm{E}[r^e_{i,t}] = \lambda_0 + \beta_{i,SDF}\lambda_{SDF}, \tag{19}$$

[21]The Index of Consumer Expectations is a component of the University of Michigan Consumer Sentiment Index. It reflects the survey answers to the questions on how consumers view the prospects for their own financial situation over the next 12 months, on how they view the prospects for the general economy over the next 12 months, and on how they view the prospects for the economy over the next 5 years.

where $\beta_{i,SDF}$ is the beta to the stochastic discount factor innovations measured conditional on agent's information. As discussed in Section 2.1, these innovations can be written as:

$$m_{t,t+1} - \mathrm{E}\left[m_{t,t+1} \,|\, \mathcal{I}_t\right] \approx m_\varepsilon' \varepsilon_{t+1},$$

where $\varepsilon_t = \left[\varepsilon_{0,t}\, \varepsilon_{1,t}\, \varepsilon_{4,t}\, \varepsilon_{8,t}\, \varepsilon_{z,t}\, \varepsilon_{m,t}\right]'$ and m_ε is a vector of coefficients determined by the model.[22] To better gauge the contribution of news to aggregate risk we also consider the counterfactual cases where only the correctly anticipated (fundamental) or only the pure belief component of news is active. We disentangle the fundamental and belief components of news by considering appropriate combinations of news and surprise shocks $\varepsilon_{0,t}\, \varepsilon_{1,t}\, \varepsilon_{4,t}\, \varepsilon_{8,t}$, as shown in Chahrour and Jurado (2018); see also Appendix A.1. Finally, because the dynamics of the model, and thus the identification of news shocks, are effectively independent of γ, we can simultaneously consider a special case with $\gamma = 1$, which corresponds to time-additive preferences. In this case, only the innovations to realized consumption growth enter the stochastic discount factor, as can be seen from (11). As a result, we have

$$\mathrm{E}[r^e_{i,t}] = \lambda_0 + \beta_{i,C}\lambda_C, \tag{20}$$

where $\beta_{i,C}$ is the beta to the innovations in consumption given by

$$c_{t+1} - \mathrm{E}\left[c_{t+1} \,|\, \mathcal{I}_t\right] \approx c_\varepsilon' \varepsilon_{t+1}.$$

3.1 Book-to-Market and Size Portfolios

To begin, we consider the 25 Fama-French size and book-to-market sorted portfolios, a cross-section that has previously challenged the factors rooted in the economic theory.[23] Panel

[22] We use the first order approximation in our discussion for expositional convenience. All the reported numerical results are based on the full second-order perturbation solution. See also Malkhozov (2014) on how to compute risk-adjustments in log-linearized macroeconomic models.

[23] The static CAPM of Sharpe (1964) and Lintner (1965) and the consumption CAPM (C–CAPM) of Breeden (1979) continue to perform poorly during our sample period in tests that do not take into account agents' information; see Table A.1 in the Appendix. For instance, as in many past studies, we find that the CAPM market factor is negatively priced, contrary to the theoretical prediction.

A of Figure 6 graphically summarizes the performance of the stochastic discount factor innovations in explaining the average expected returns of these portfolios. Innovations have the explanatory power across both sorting dimensions. Moreover, the observed relationship between factor beta and expected return is not driven by outlier portfolios.

[Insert Figure 6 about here]

Panel A of Table 4 examines the performance of the factor more formally. Accounting for agents' information in constructing stochastic discount factor innovations leads to an R^2 of 40%. Following Kan et al. (2013), we compute the sampling variability in the R^2s and find that it is 1.5 standard deviation away from zero.

The zero-beta rate and risk premium estimates further support our conclusions. We report $\widehat{\lambda}$s and associated t-ratios. In particular, we report the Fama and MacBeth t-statistic, followed by the GMM-corrected t-statistic which accounts for estimation error in the betas; see Shanken (1992) and Jagannathan and Wang (1998). The SDF innovation coefficient is negative and statistically significant, in line with theoretical predictions. In addition, the zero-beta rate is not significantly different from the risk-free rate.

[Insert Table 4 about here]

A standard concern in asset pricing models with macro factors is that these factors may display a large measurement error component, and therefore not have enough comovement with test asset returns to produce a reliable estimate of the risk premium. Such factors are regarded as weak ones, as discussed in, e.g., Kan and Zhang (1999) and Kleibergen (2009). To address this issue, we test whether the factor betas are jointly significantly different from a constant. At conventional significance levels, we reject the hypothesis that all betas are equal to each other and, hence, find support for statistically significant spread in the betas across portfolios. See Appendix A.7 for a more detailed discussion of these results.

Overall, this is a remarkable performance for a one-factor macro-based asset pricing model. Furthermore, Appendix A.8 and Appendix Tables A.2-A.3 show that our results are robust to alternative subsamples and the inclusion of industry portfolios.

The second and third specifications in Panel A of Table 4 point to the critical role of news shocks, and specifically of the pure belief component of news, for the pricing of the size and book-to-market sorted portfolios. Indeed, as reported in column (2), if we shut down the variation in pure beliefs keeping only the fundamental component of news, the pricing performance worsens dramatically. In the following sections we further explore the roles of the fundamental and pure beliefs components by considering both alternative cross sections and the components of the book-to-market strategy.

3.2 Bond and Duration-Sorted Portfolios

In this section, we explore alternative cross sections of test assets.

First, Panel B of Table 4 reports results for a cross-section of stock and bond portfolios. In particular, we include five value-weighted quintile portfolios sorted on their book-to-market ratio from Fama and French (1992), the value-weighted stock market return from CRSP (NYSE, Amex, and Nasdaq), and five zero-coupon nominal government bond portfolios with maturities 1, 2, 5, 7, and 10 years from CRSP. Focusing on the pricing errors, our one-factor model reduces the MAPE across the 11 stock and bond portfolios from 3.1% (the average pricing error to be explained in our sample period) to 1% per year. For comparison, the model of Koijen, Lustig and Van Nieuwerburgh (2017) attains a MAPE of 0.50% with three tradable risk factors which contrasts with our single macroeconomic factor model.

Second, Panel C of Table 4 presents results for the duration-sorted portfolios constructed by Weber (2018). The author sorts stocks into ten portfolios based on a measure of firm-level cash flow duration and shows that low-duration stocks outperform high-duration stocks by 1.10% per month. Importantly, Weber (2018) shows that well-known risk factors, including the ultimate consumption risk of Parker and Julliard (2005) and Malloy, Moskowitz and Vissing-Jorgensen (2009), cannot explain this novel cross section. In contrast, our SDF innovations remain statistically significant and continue to perform well in explaining this challenging cross section.

Turning to the second and third specification in Panels B and C, we observe that the correctly anticipated changes in fundamentals play a more important role than the variation in pure beliefs for the cross sections containing bond or duration-sorted stock portfolios. For instance, as we move from specification (1) to (2) for duration portfolios in Panel C, we observe that the R^2 increases and its variability decreases, while the premium remains statistically significant with a magnitude comparable across specifications. On the other hand, when we move from specification (1) to (3) the premium halves and the value of the R^2 is dwarfed by its variability.

The findings above contrast with the results for the 25 Fama-French size and book-to-market sorted portfolios in Section 3.1. Lettau and Wachter (2007) propose a duration-based explanations for the value premium that appeals to the differential timing of cash flows between value and growth firms. This view has been recently challenged by, for instance, Chen (2017) who shows that growth stocks do not have substantially higher future cash-flow growth rates than value stocks. Our results suggest that duration and value are two different phenomena. Value portfolios are primarily related to the pure beliefs component. Duration-sorted portfolios are instead more exposed to correctly anticipated changes in fundamentals, and in this respect behave similarly to bond portfolios.

Finally, for the case of bond and stock portfolios in Panel B, the improvement in the pricing error as we move from specification (1) to (2) masks important cross-sectional differences. In Appendix A.9 we display, for different SDF specifications, the pricing errors of the individual portfolios as well as the mean absolute pricing errors for various groups of assets. The results show that, as we move from our baseline SDF to the model where only the correctly anticipated (fundamental) component of news is active, the MAPE of bond portfolios decreases by half from 0.956 to 0.592, while the pricing of book-to-market portfolios slightly worsens. Our analysis sheds light on the trade-off posed by this cross-section recently proposed by Koijen et al. (2017): the pricing of bonds assigns an important role to the fundamental component of news, while the pricing value portfolios assigns an important role to beliefs. The type and number of test assets turns out to be an important choice variable. Including bonds along equity value portfolios increases the weight that it is assigned to the fundamental component.[24]

[24]The MAPE of the value-growth spread portfolio is large at 2.1% when the belief-driven SDF is employed. This is because we are including bond portfolios. When we remove bonds, the MAPE for the value-growth spread portfolio drops at 1.1% if the pure beliefs SDF is employed. On the other hand, removing bond portfolios from

In turn, increasing the number of portfolios sorted on book-to-market used in the regressions, increases the weight that is assigned to the pure beliefs component.

3.3 Components of Market-to-Book

In this section, we further examine the value premium through the lens of the recent decomposition proposed by Golubov and Konstantinidi (2019). The authors follow Rhodes-Kropf et al. (2005) and decompose market-to-book into market-to-*value* and *value*-to-book components, where *value* is a multiples-based measure of the fair firm value. The authors show that the market-to-value component is the sole driver of value strategy returns. This result can help discriminate more sharply between competing explanations of the value premium. That is, a promising candidate should price the market-to-value portfolios.

For our baseline results we use the comprehensive decomposition of Golubov and Konstantinidi (2019): i.e., the market-to-value component is further decomposed into stock price deviations from contemporaneous peer-implied valuations (firm-specific error) and deviations of the latter from valuations implied by long-run industry multiples (sector error). The authors show that the value premium is captured entirely by the firm-specific error, whereas sector error exhibits no significant association with future stock returns. We report results for the simpler decomposition into market-to-value (total error) and value-to-book components in Appendix A.10 and Appendix Table A.4.[25]

Table 5 shows that the premium for our aggregate risk factor is statistically significant when we use portfolios sorted on firm-specific error. In contrast, this is not the case for portfolios sorted on sector errors or value-to-book. In addition, Appendix A.7 shows that innovations in our factors generate a statistically significant spread in betas only for the market-to-value portfolios.

[Insert Table 5 about here]

Similar to our results in Section 3.1, the second and third specifications in Table 5 point to

the fundamental-driven SDF does not alter the pricing errors which continue to stay high at 2.4%.

[25] We follow Golubov and Konstantinidi (2019) and use return-weighted portfolios as test assets.

the important role of news shocks, and specifically of the pure belief component of news, for the pricing of portfolios sorted on firm-specific error. Indeed, as reported in column (2), if we shut down the variation in pure beliefs keeping only the fundamental component of news, the pricing performance worsens dramatically. This role of the variation in pure beliefs is in line with Golubov and Konstantinidi (2019), who argue that mechanisms related to investors' expectations are the most likely explanation for the value premium. Through the lens of our model, value stocks do well when agents believe productivity will improve (but it won't), and vice versa. Importantly, our explanation is not behavioral and does not require over-extrapolation by agents. Forecast errors arise naturally from a fully rational equilibrium model with agents facing a signal extraction problem.

3.4 Pricing with Consumption Innovations

In this section, instead of the stochastic discount factor implied by our estimate of γ, we consider the case with $\gamma = 1$, in which innovations to consumption represent the aggregate risk factor. This exercise is consistent with the rest of our analysis because of the role played by γ – this parameter determines the unconditional means of the term structure slope and of the aggregate price-to-dividend ratio in the model, but has no bearing on the properties of the shocks ε_t in relation to the cross-section of asset returns. The special case allows us gauge the role of preferences for our results. Moreover, to shed additional light on our results, consumption innovations can be naturally compared to consumption growth, an observed benchmark.

Table 6 reports the results of the cross-sectional asset pricing tests in which we use consumption innovations as the sole pricing factor. Across alternative cross sections, the risk premiums are positive and statistically significant, as predicted by the theory. In addition, the zero-beta rate for consumption innovations is not significantly larger than the risk-free rate. Consumption innovations have considerable explanatory power in all considered cross sections, with R^2 reaching 44% for the 25 Fama-French size and book-to-market portfolios, and 64% for the Golubov and Konstantinidi (2019) market-to-book sorted portfolios. Panel B of Figure 6 graphically summarizes the performance of the consumption innovations in explaining the average expected returns of the 25 Fama-French portfolios.[26]

A first insight gained from using consumption innovations is that recursive preferences do not play a key role for our results. The equally good performance of the realized consumption innovations compared to the innovations in the more general recursive stochastic discount factor is perhaps not surprising. The novelty of our factors lies in the identified shocks ε_t which represent the true innovations to the agents' information set. Innovations in the recursive stochastic discount factor and innovations in consumption growth can be intuitively understood as a somewhat different but overall similar combinations of these shocks: the stochastic discount factor implied by recursive utility puts relatively more weight on the longer-horizon news whereas realized consumption reacts somewhat more moderately to changes in expected future productivity.[27] Yet, even if the shock loadings are partly misspecified relative to the true stochastic discount factor, we show that a better identification of the true innovations to agents' information set in itself improves on our ability to explain the cross-section of expected returns.

Next, consumption innovations $c_{t+1} - \mathrm{E}[c_{t+1} \,|\, \mathcal{I}_t]$ can be compared to the consumption growth rate $c_{t+1} - c_t$. The difference between these two series represents the expected consumption growth $\mathrm{E}[c_{t+1} - c_t \,|\, \mathcal{I}_t]$. Note that the difference between consumption growth and consumption innovations resulting from our estimation is closely aligned with the expectation measures from the Michigan survey of consumers; see Figure 4 and the related discussion in Section 2.3. Given the poor performance of consumption growth in unconditional C–CAPM tests, accounting for agents' conditional information is key for the consumption innovations performance in explaining the cross-section of asset returns.[28]

Finally, it is also insightful to compare consumption innovations to consumption growth over several subsequent quarters. In an important paper, Parker and Julliard (2005) argue that the risk of an asset is better measured by the covariance of its return with consumption growth

[26] In addition, Table A.5 in the Appendix shows that our results on the role of the pure belief component of news for the value premium continue to hold with consumption innovations.

[27] Note that most of the variation in expectations about future productivity in the model occur within the business cycle horizon, and not at the very long horizon as in the long-run risk models.

[28] Note that, similar to the observed consumption growth rate and unlike consumption innovations, the consumption growth rate implied by the model also has little explanatory power for the cross-section of expected returns. This is not surprising, given the model's good match of observed macroeconomic dynamics.

over the quarter of the return and several subsequent quarters, namely $\mathrm{Cov}\left(r^e_{i,t+1}, c_{t+1+h} - c_t\right)$. A similar measure is also employed by Malloy, Moskowitz and Vissing-Jorgensen (2009). In the context of our model, consumption growth over several quarters, or ultimate consumption, can be interpreted as a proxy for the realization of news shocks that determine fundamentals in subsequent quarters. To see how news shocks can give rise to ultimate consumption risk, consider the model-implied covariances between stock returns and consumption innovations with subsequent consumption growth. First, the model with news captures well the covariance pattern between market returns and future consumption growth documented in Parker and Julliard (2005); see Panel A of Figure 5 and the related discussion in Section 2.3. Second, Panel B of of Figure 5 shows a similar horizon pattern in the covariance between consumption innovations – the true measure of aggregate risk in the model which reflect the reaction of consumption to news about future productivity – and future consumption growth.

To compare the two competing measures of risk – ultimate consumption and consumption innovations – we run the following cross-sectional regressions

$$\mathrm{E}[r^e_{i,t}] = \lambda_0 + \beta_{i,C}\lambda_C + \beta_{i,PJ}\lambda_{PJ}, \tag{21}$$

where we choose $h = 11$ quarters as in Parker and Julliard (2005), and the betas are estimated from two separate univariate regressions.[29] Table 7 reports the results from estimating this two-factor model.[30] We find that λ_{PJ} is not significant, whereas the price of our consumption innovation, λ_C, remains significant. Moreover, the R^2 from a regression that includes only consumption innovations is 0.43; thus, adding ultimate consumption increases the cross-sectional R^2 by just 1 percentage point.[31] We conclude that our news-driven measure of risk captures

[29]As argued in Kan et al. (2013), using separate, simple regressions ensures that if the estimated price of risk λ_C is significant then one can conclude that consumption innovations contributes to explaining cross-sectional variation in returns after controlling for ultimate consumption. One cannot draw this conclusion in the case of multiple regression betas, because consumption innovations betas also change when ultimate consumption is added, unless the two risk factors are uncorrelated.

[30]Table 7 also reports results for the one-factor model with ultimate consumption: we find a positive price of ultimate consumption risk that is marginally insignificant. The R^2s are comparable to those obtained in Parker and Julliard (2005) despite the different sample period.

[31]Note that the sample is different from that in Table 6 since we loose about 3 years of data to compute the forward looking ultimate consumption factor.

macroeconomic risk more adequately than ultimate consumption. This result is in line with our interpretation of ultimate consumption as imperfect proxy for the realization of news shocks.

3.5 Pricing with and without News

News shocks are critical for our cross-sectional results. Tables 4 and 5 already point to this fact since, whenever we switch off the priced component of news (for instance, the belief-driven part of news in the case of portfolios sorted on book-to-market), the pricing performance deteriorates substantially. In this section, we explore the role of news shocks in more detail.

First, news shocks on their own have substantial explanatory power for the cross section of asset returns. Moreover, news at both short and longer horizon are important. In our baseline results above we aggregated news shocks and other structural shocks (surprise in permanent and transitory productivity, and monetary shocks) into a single risk factor using model-implied restrictions. Instead, Table A.6 in the Appendix examines the individual contribution of news shocks with different anticipation horizons. To do so, we consider a specification where we do not restrict the way news shocks enter the stochastic discount factor and allow news at each horizon to represent a potentially independent source of risk with its own risk premium:

$$E[r^e_{i,t}] = \lambda_0 + \lambda_1 \beta_{i,1} + \lambda_4 \beta_{i,4} + \lambda_8 \beta_{i,8}, \tag{22}$$

where $\beta_{i,j}$ is the beta of returns on asset i with the j-period anticipated news. Consider, for instance, the case of the 25 Fama-French portfolios in Panel A. The specification with three news shocks as risk factors attains an R^2 of 52% and a RMSE of 1.8%, a performance similar to our baseline results. Consistent with the intuition that positive news about future productivity decrease marginal utility, news at all horizons carry a positive risk premium. This premium decreases monotonically with news horizon. Finally, both one- and eight-quarter news are highly statistically significant.

Second, to further gauge the role of news, we re-estimate a version of our structural model that does not allow for news shocks. We shows that the pricing performance of the factors resulting from the new estimation worsens along several dimensions compared to the baseline case. For instance, as shown in Table A.7 in the Appendix, in the case of the 25 Fama-French portfolios the SDF innovation achieves a worse cross-sectional fit, with the R^2 decreasing from 40% to 23% and its variability becoming so large that it is hard to distinguish the one-factor model from a benchmark that includes only a constant risk premium across all assets. Similarly, the R^2 for the specification with consumption innovations as risk factor also drops and the risk premium for consumption innovations loses its statistical significance.

4 Conclusion

In this paper, we show the importance of agents' expectations about the forces driving the business cycle for our understanding of aggregate risk. We show that accounting for changes in agents' information due to the arrival of news results in better-specified aggregate risk factor innovations. A better identification of aggregate macroeconomic risk, in turn, improves our ability to explain the cross section of expected returns, helping resolve an important failure of the consumption-based asset pricing framework. For instance, we find that consumption growth innovations filtered from our news-driven model are priced in the cross-section of stock and bond returns.

Distinguishing between news that materialize and those that do not sheds a new light on various cross sections of expected returns that continue to challenge the asset pricing theory. Whereas exposure to correctly anticipated changes in future fundamentals is important for cash flow duration portfolios, market-to-book and market-to-value strategies load on the component of expectations that does not materialize, i.e. pure beliefs. Importantly, in our setting agents' expectation errors arise naturally in a fully rational equilibrium model with agents facing a signal extraction problem.

Overall, accounting for agents' expectations offers a coherent way of thinking about aggregate macroeconomic fluctuations and asset-pricing anomalies.

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5 Tables

TABLE 1: **Model Parameters.** This table reports the calibrated (Panel A) and estimated (Panel B) model parameters. Note that the parameter values of μ_a, σ_a, σ_{1Q}, σ_{4Q}, σ_{8Q}, σ_z, and σ_m are expressed in percent. The estimated parameters are from the second step in a GMM estimation using the optimal weighting matrix with 10 lags in the Newey-West estimator. Asymptotic standard errors for the estimated parameters are reported in parentheses.

Panel A: Calibrated Parameters

Firm:			*Monetary Policy:*		
δ	capital depreciation	0.030	Π	steady-state inflation	1.008
α	capital share	0.360	ρ_r	persistence short rate	0.70
θ	price rigidity	0.760	ϕ_π	TR coefficient inflation gap	1.500
ρ_w	wage rigidity	0.900	ϕ_{y1}	TR coefficient output growth	0.700
χ	leverage	3.000	ϕ_{y2}	TR coefficient output gap	0.080

Panel B: Estimated Parameters

Preferences:			*Shocks:*		
β	time discount	0.995	μ_a	steady-state productivity growth	0.401
		(0.001)			(0.031)
γ	curvature	-85.000	ρ_a	AR(1) productivity	0.360
		(4.142)			(0.040)
ψ	IES	1.650	σ_a	volatility productivity	0.505
		(0.032)			(0.013)
η	Frisch elasticity	1.800	σ_{1Q}	volatility 1Q news	0.498
		(0.039)			(0.023)
			σ_{4Q}	volatility 4Q news	0.501
					(0.038)
Firm:			σ_{8Q}	volatility 8Q news	0.199
ε	mark-ups	13.500			(0.029)
		(0.238)	ρ_z	AR(1) technology	0.975
ζ	capital adjustment costs	0.940			(0.011)
		(0.008)	σ_z	volatility technology	0.722
					(0.028)
			σ_m	volatility monetary policy	0.210
					(0.016)

TABLE 2: **Unconditional Moments.** This table reports the mean, standard deviations and correlations for observable variables in the baseline model. We split the model variables into macro variables (Panel A) and asset prices (Panel B). We further differentiate between moments which we target during our estimation and non-targeted moments. The sample period for the data is 1970.Q1 to 2016.Q4. Macro data such as output, consumption, investment and wages are in logs, HP-filtered, and multiplied by 100 to express them in percentage deviation from trend. Further, we remove a secular trend from the price-to-dividend (PD) ratio to focus on business-cycle fluctuations. Asset prices, except the PD ratio, are annualized and expressed in percentages. The squared brackets contain the 5% and 95%-confidence bands for the model implied moments taking into account parameter uncertainty (the model is simulated using 200 different parameter draws).

Panel A: Macro Variables

	Model			Data		
	SD	AR(1)	Cor(.,yt)	SD	AR(1)	Cor(.,yt)
Targeted Moments:						
Output	2.94	0.85	1.00	1.54	0.87	1.00
	[2.77,3.28]	[0.84,0.86]				
Consumption	1.17	0.91	0.82	1.27	0.89	0.88
	[1.10,1.29]	[0.89,0.92]	[0.75,0.86]			
Investment	7.63	0.78	0.98	7.07	0.85	0.92
	[7.06,8.83]	[0.77,0.80]	[0.96,0.98]			
Inflation	1.20	0.87	0.06	0.61	0.89	0.11
	[0.81,1.52]	[0.84,0.92]	[0.05,0.07]			
Non-Targeted Moments:						
Wages	0.63	0.92	0.20	0.93	0.68	0.09
	[0.59,0.70]	[0.91,0.93]	[0.18,0.22]			

Panel B: Asset Prices

	Model				Data			
	Mean	SD	AR(1)	Cor(.,yt)	Mean	SD	AR(1)	Cor(.,yt)
Targeted Moments:								
Nominal Rate 1Q	5.61	3.75	0.92	0.06	5.62	3.88	0.94	0.22
	[4.41,7.63]	[2.75,6.07]	[0.88,0.95]	[0.03,0.09]				
Slope	1.23	1.82	0.84	-0.29	1.23	2.09	0.77	-0.47
	[0.84,1.98]	[1.65,2.12]	[0.81,0.85]	[-0.34,-0.25]				
PD Ratio	3.04	12.68	0.97	-0.19	3.64	24.83	0.93	0.10
	[0.86,4.85]	[10.26,18.23]	[0.96,0.99]	[-0.23,-0.13]				
Non-Targeted Moments:								
Nominal 5Y	6.62	2.65	0.96	-0.07	6.34	3.06	0.97	0.00
	[5.44,9.00]	[1.65,4.89]	[0.94,0.98]	[-0.10,-0.03]				
Nominal 10Y	6.84	2.11	0.98	-0.09	6.84	2.71	0.97	-0.05
	[5.62,9.53]	[1.21,4.23]	[0.95,0.98]	[-0.12,-0.05]				
Real 2Y	1.71	0.70	0.89	0.04	1.87	1.80	0.89	0.10
	[1.41,1.96]	[0.66,0.77]	[0.89,0.90]	[0.02,0.06]				
Real Equity Returns	8.23	7.12	-0.04	-0.23	5.66	18.14	0.07	-0.08
	[7.25,9.40]	[6.73,7.61]	[-0.04,-0.03]	[-0.21,-0.25]				

TABLE 3: **The Role of Structural Shocks.** Panel A reports the fraction of the total variance obtained from simulating the model with only a subset of structural shocks enabled. Panel B reports a variance decomposition of permanent productivity shocks into surprises and news, and fundamental and pure belief components, respectively. Using the estimated parameters from Table 1, we approximate the model to the second-order around the deterministic steady state and simulate from the ergodic mean for 1000 periods with a burn-in of 2000 periods. The fractions of the total variance induced by individual shocks may not add up to 100 percent due to the presence of the non-linear terms in the approximation.

Panel A: The Role of Structural Shocks (% of total variance)

			Macro Variables			
	Output	Consumpt.	Invest.	Wages	Inflation	
Productivity (permanent)	44.11	54.95	37.51	55.83	14.86	
Productivity (transitory)	47.12	45.25	49.68	40.64	86.97	
Monetary	12.74	7.48	13.38	5.43	2.38	
			Asset Prices			
	Nomin. 1Q	Nomin. 10Y	Slope	Real 1Q	PD-Ratio	Returns
Productivity (permanent)	5.63	0.79	16.89	60.11	19.67	96.70
Productivity (transitory)	94.22	99.41	77.89	47.51	83.51	2.37
Monetary	0.94	0.01	3.61	2.57	0.92	0.24

Panel B: Information Set Decomposition (% of total variance)

			Macro Variables			
	Output	Consumpt.	Invest.	Wages	Inflation	
Surprises	39.34	43.24	36.85	36.26	35.12	
News	60.66	56.76	63.15	63.74	64.88	
Fundamental	96.54	93.70	92.57	98.80	85.23	
Beliefs	3.46	6.30	7.43	1.20	14.77	
			Asset Prices			
	Nomin. 1Q	Nomin. 10Y	Slope	Real 1Q	PD-Ratio	Returns
Surprises	27.18	29.03	27.33	29.59	19.28	30.31
News	72.82	70.97	72.67	70.41	80.72	69.69
Fundamental	70.70	80.15	70.93	93.25	77.59	31.05
Beliefs	29.30	19.85	29.07	6.75	22.41	68.95

TABLE 4: **Cross Section of Asset Prices.** The table reports results of the cross-sectional regression

$$\overline{R_i^e} = \lambda_0 + \beta_i \lambda_{SDF} + \alpha_i,$$

where $\overline{R_i^e}$ is the mean excess return of portfolio i and β_i is the factor beta of portfolio i estimated in the first-pass regression. In Panel A the models are estimated using the models are estimated using quarterly excess returns on the 25 Fama-French size and book-to-market ranked portfolios. In Panel B the models are estimated using five book-to-market sorted quintile stock portfolios, the value-weighted market portfolio, and six maturity-sorted Fama bond portfolios obtained from the Center for Research in Security Prices Treasury. In Panel C the models are estimated using quarterly excess returns on the ten portfolios sorted on cash flow duration from Weber (2018). The table reports the estimates of the factor risk premia $\widehat{\lambda}$ and the constant term, Fama and MacBeth (1973) standard errors (in parentheses), and the GMM-VARHAC standard errors (accounting for the sampling error in the betas) for these estimates (in braces). The second to last column reports asymptotic p-values of chi-squared tests of the null hypothesis that all pricing errors are jointly zero (Joint p-value). To compute the test statistic we use the OLS covariance matrix of $\widehat{\alpha}$. The last column reports the R^2 of the cross-sectional regression and its standard error (under the assumption that $0 < R^2 < 1$). We report in bold font values that are significant at the 10% level. We also report the root mean square alpha (RMSE) and the mean absolute pricing error (MAE) across all test assets. These are expressed as percentages per year. The data are quarterly from March 1970 through June 2016.

Constant	(1) λ_{SDF}	(2) λ_{SDF} funda.	(3) λ_{SDF} beliefs	RMSE	MAPE	Joint p-value	R^2
		Panel A: Book-to-Market and Size Portfolios					
0.016	**-0.471**			2.019	1.493	0.000	0.40
(0.008)	(0.159)						(0.27)
{0.011}	{0.244}						
0.009		-0.144		2.395	1.834	0.000	0.14
(0.008)		(0.078)					(0.38)
{0.010}		{0.091}					
0.024			**-0.319**	2.076	1.557	0.000	0.36
(0.008)			(0.121)				(0.29)
{0.010}			{0.163}				
		Panel B: Bond and Stock Portfolios					
0.008	**-0.756**			1.139	1.029	0.003	0.89
(0.002)	(0.310)						(0.12)
{0.003}	{0.449}						
0.005		**-0.162**		1.248	0.961	0.008	0.87
(0.002)		(0.071)					(0.17)
{0.003}		{0.094}					
0.016			-0.885	2.755	2.428	0.004	0.34
(0.005)			(0.363)				(0.32)
{0.015}			{1.225}				
		Panel C: Duration Portfolios					
0.048	**-0.689**			2.618	1.576	0.000	0.53
(0.012)	(0.160)						(0.47)
{0.019}	{0.288}						
-0.015		**-0.788**		1.772	1.614	0.000	0.79
(0.023)		(0.179)					(0.54)
{0.079}		{-0.469}					
0.058			**-0.361**	3.108	2.068	0.000	0.34
(0.010)			(0.095)				(0.43)
{0.014}			{0.127}				

TABLE 5: **Components of the Market-to-Book.** The table reports results of the cross-sectional regression

$$\overline{R_i^e} = \lambda_0 + \beta_i \lambda_{SDF} + \alpha_i,$$

where $\overline{R_i^e}$ is the mean excess return of portfolio i and β_i is the factor beta of portfolio i estimated in the first-pass regression. In Panel A we use quarterly excess returns on 10 market-to-value (firm-specific error) ranked portfolios. In Panel B we use quarterly excess returns on 10 market-to-value (sector error) ranked portfolios. In Panel C we use quarterly excess returns on 10 value-to-book ranked portfolios. Data on portfolios in all Panels are from Golubov and Konstantinidi (2019). The table reports the estimates of the factor risk premia $\widehat{\lambda}$ and the constant term, Fama and MacBeth (1973) standard errors (in parentheses), and the GMM-VARHAC standard errors (accounting for the sampling error in the betas) for these estimates (in braces). The second to last column reports asymptotic p-values of chi-squared tests of the null hypothesis that all pricing errors are jointly zero (Joint p-value). To compute the test statistic we use the OLS covariance matrix of $\widehat{\alpha}$. The last column reports the R^2 of the cross-sectional regression and its standard error (under the assumption that $0 < R^2 < 1$). We report in bold font values that are significant at the 10% level. We also report the root mean square alpha (RMSE) and the mean absolute pricing error (MAE) across all test assets. These are expressed as percentages per year. The data are quarterly from March 1970 through June 2013.

Constant	(1) λ_{SDF}	(2) λ_{SDF} funda.	(3) λ_{SDF} beliefs	RMSE	MAPE	Joint p-value	R^2
		Panel A: Market-to-value (firm-specific error)					
0.026	**-0.656**			2.286	1.742	0.001	0.52
(0.010)	(0.203)						(0.38)
{0.016}	{0.377}						
0.018		-0.167		2.908	2.404	0.001	0.04
(0.008)		(0.088)					(0.32)
(0.012)		(0.128)					
0.032			**-0.443**	2.180	1.699	0.001	0.46
(0.010)			(0.131)				(0.33)
{0.013}			{0.157}				
		Panel B: Market-to-value (sector error)					
0.027	0.273			0.723	0.617	0.560	0.45
(0.009)	(0.232)						(0.63)
{0.010}	{0.270}						
0.030		0.073		0.808	0.627	0.517	0.31
(0.011)		(0.089)					(0.75)
{0.009}		{0.102}					
0.027			0.226	0.723	0.617	0.560	0.30
(0.009)			(0.173)				(0.45)
{0.010}			{0.203}				
		Panel C: Value-to-book					
0.026	-0.151			0.685	0.561	0.391	0.10
(0.010)	(0.386)						(0.53)
{0.010}	{0.454}						
0.021		-0.108		0.625	0.492	0.380	0.25
(0.015)		(0.167)					(0.89)
{0.018}		{0.198}					
0.028			-0.073	0.709	0.569	0.350	0.04
(0.009)			(0.298)				(0.31)
{0.010}			{0.332}				

TABLE 6: **Pricing with Consumption Innovations.** The table reports results of the cross-sectional regression

$$\overline{R_i^e} = \lambda_0 + \beta_i \lambda_C + \alpha_i,$$

where $\overline{R_i^e}$ is the mean excess return of portfolio i and β_i is the factor beta of portfolio i estimated in the first-pass regression. The model is estimated using, respectively, quarterly excess returns on the 25 Fama-French size and book-to-market ranked portfolios; 10 market-to-book ranked portfolios, 10 market-to-value (total error) ranked portfolios, and 10 market-to-value (firm-specific error) ranked portfolios from Golubov and Konstantinidi (2019); five book-to-market sorted quintile stock portfolios, the value-weighted market portfolio, and six maturity-sorted Fama bond portfolios obtained from the Center for Research in Security Prices Treasury; and the ten portfolios sorted on cash flow duration from Weber (2018). The table reports the estimates of the factor risk premia $\widehat{\lambda}$ and the constant term, Fama and MacBeth (1973) standard errors (in parentheses), and the GMM-VARHAC standard errors (accounting for the sampling error in the betas) for these estimates (in braces). The second to last column reports asymptotic p-values of chi-squared tests of the null hypothesis that all pricing errors are jointly zero (Joint p-value). To compute the test statistic we use the OLS covariance matrix of $\widehat{\alpha}$. The last column reports the R^2 of the cross-sectional regression and its standard error (under the assumption that $0 < R^2 < 1$). We report in bold font values that are significant at the 10% level. We also report the root mean square alpha (RMSE) and the mean absolute pricing error (MAE) across all test assets. These are expressed as percentages per year. The data are quarterly from March 1970 through December 2016.

	Constant	λ_C	RMSE	MAPE	Joint p-value	R^2
25 Fama-French	0.007 (0.008) {0.013}	**0.003** (0.001) {0.001}	1.949	1.347	0.000	0.44 (0.29)
Market-to-book	0.021 (0.009) {0.017}	**0.004** (0.002) {0.002}	1.638	1.169	0.003	0.64 (0.41)
Market-to-value (total error)	0.019 (0.009) {0.018}	**0.006** (0.002) {0.003}	2.110	1.540	0.000	0.47 (0.55)
Market-to-value (firm-specific error)	0.020 (0.009) {0.017}	**0.005** (0.001) {0.002}	2.049	1.471	0.001	0.52 (0.36)
Bond and Stock	0.004 (0.002) {0.003}	**0.003** (0.001) {0.001}	1.134	0.993	0.005	0.89 (0.13)
Duration	0.026 (0.014) {0.033}	**0.006** (0.001) {0.003}	2.551	1.500	0.000	0.55 (0.54)

TABLE 7: **Comparison with Long-run Consumption.** The table reports results of the cross-sectional regression

$$\overline{R_i^e} = \lambda_0 + \beta_i \lambda + \alpha_i,$$

where $\overline{R_i^e}$ is the mean excess return of portfolio i and β_i is the vector of factor betas of portfolio i estimated in the first-pass regression. The models are estimated using quarterly excess returns on the 25 Fama-French size and book-to-market ranked portfolios. The table reports the estimates of the factor risk premia $\widehat{\lambda}$ and the constant term, Fama and MacBeth (1973) standard errors (in parentheses), and the GMM-VARHAC standard errors (accounting for the sampling error in the betas) for these estimates (in braces). The second to last column reports asymptotic p-values of chi-squared tests of the null hypothesis that all pricing errors are jointly zero (Joint p-value). To compute the test statistic we use the OLS covariance matrix of $\widehat{\alpha}$. The last column reports the R^2 of the cross-sectional regression and its standard error (under the assumption that $0 < R^2 < 1$). We report in bold font values that are significant at the 10% level. We also report the root mean square alpha (RMSE) and the mean absolute pricing error (MAE) across all test assets. These are expressed as percentages per year. The data are quarterly from March 1970 through December 2013.

Constant	λ_C	λ_{PJ}	RMSE	MAPE	Joint p-value	R^2
0.006	**0.003**		2.045	1.427	0.000	0.43
(0.008)	(0.001)					(0.30)
{0.014}	{0.001}					
0.008		0.029	2.105	1.685	0.000	0.39
(0.009)		(0.010)				(0.30)
{0.011}		{0.018}				
0.007	**0.002**	0.010	2.009	1.496	0.000	0.44
(0.009)	(0.001)	(0.012)				(0.23)
{0.011}	{0.001}	{0.016}				

6 Figures

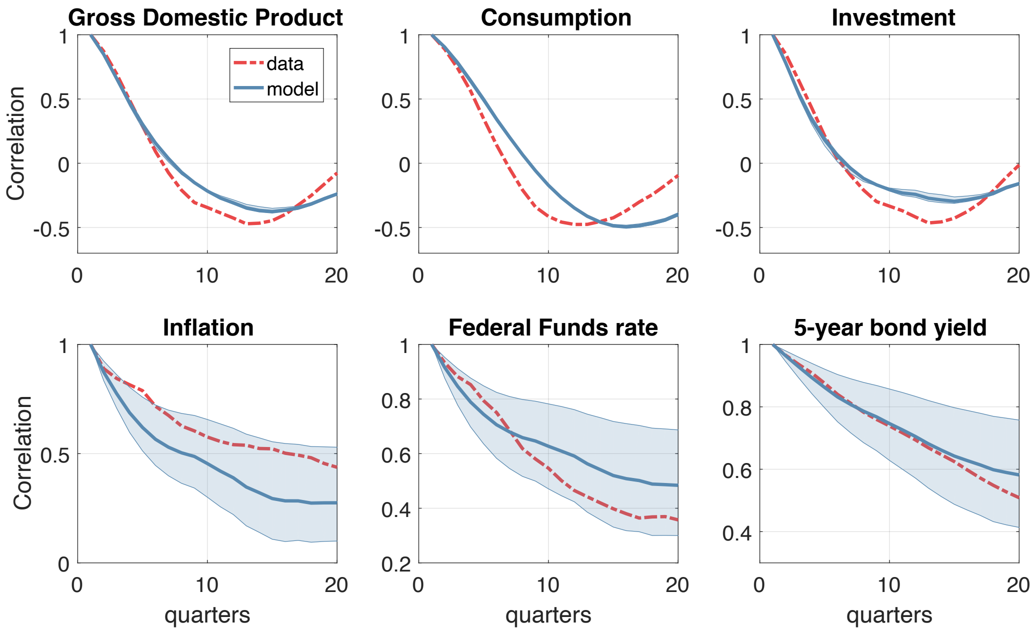


FIGURE 1: **Autocorrelation Functions**: This figure plots the autocorrelation coefficients at horizons of up to 20 quarters for output, consumption, investment, inflation, the Federal Funds rate, and the 5-year Treasury yield both in the data (red dashed line) and in the baseline model (blue solid line). The blue shaded areas correspond to 95% confidence bands of model-implied autocorrelations taking into account the parameter uncertainty.

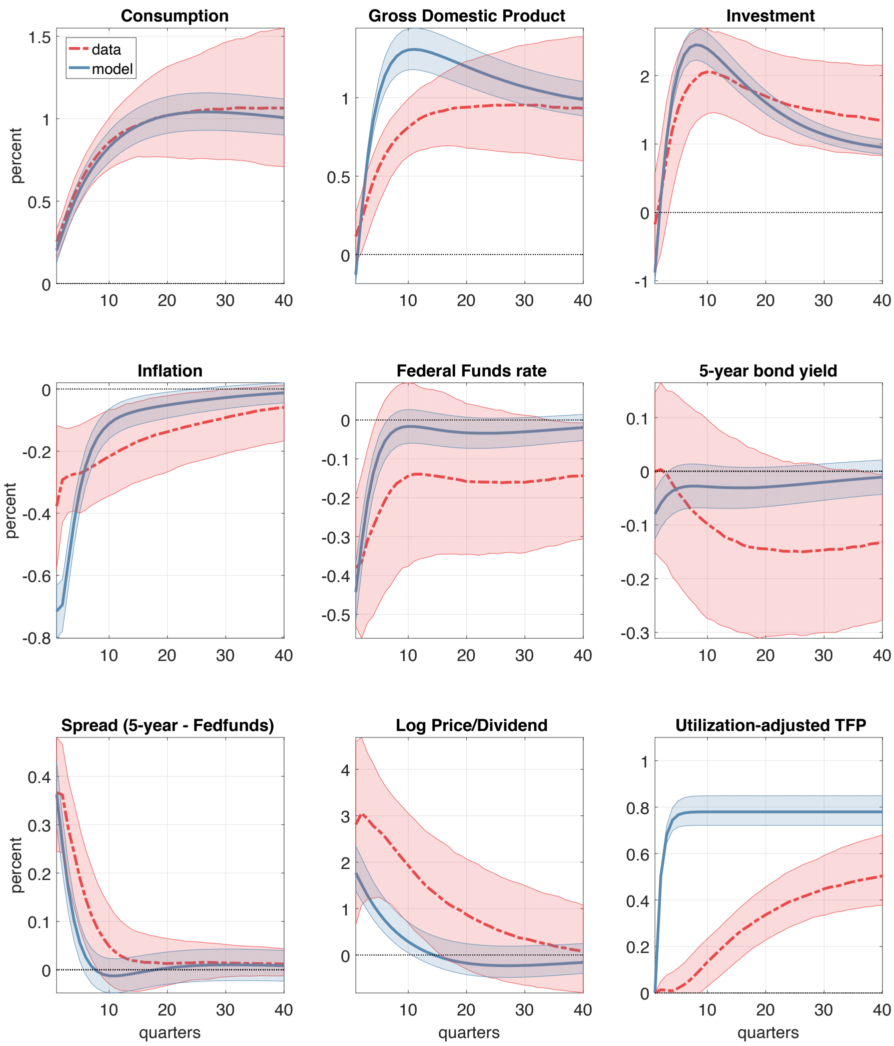


FIGURE 2: **Impulse Responses to News Shocks**: This figure plots the impulse response functions of consumption, output, investment, inflation, the Federal Funds rate, 5-year Treasury yield, the slope of the yield curve, the log price-dividend ratio and total factor productivity to a news shock both in the data (red dashed line) and the baseline model (blue solid line). The red and blue shaded areas correspond to 95% confidence bands in the data and the model, respectively. The theoretical IRFs combine the responses to the three news shocks in the model (1Q, 4Q, and 8Q news shocks) by assigning a weight of $\sigma_j^2/(\sigma_{1Q}^2+\sigma_{4Q}^2+\sigma_{8Q}^2)$ to the j-quarter news response. The theoretical responses correspond to 1.2 standard deviation news shocks (for 1Q, 4Q, and 8Q). The shock size is chosen to align the on impact response of the slope of the yield curve (5-year − Fed fund rate) in the data and the model. The empirical impulse responses to the news shock are identified over the 0-80 quarter horizon as in Barsky and Sims (2011) and Kurmann and Otrok (2013).

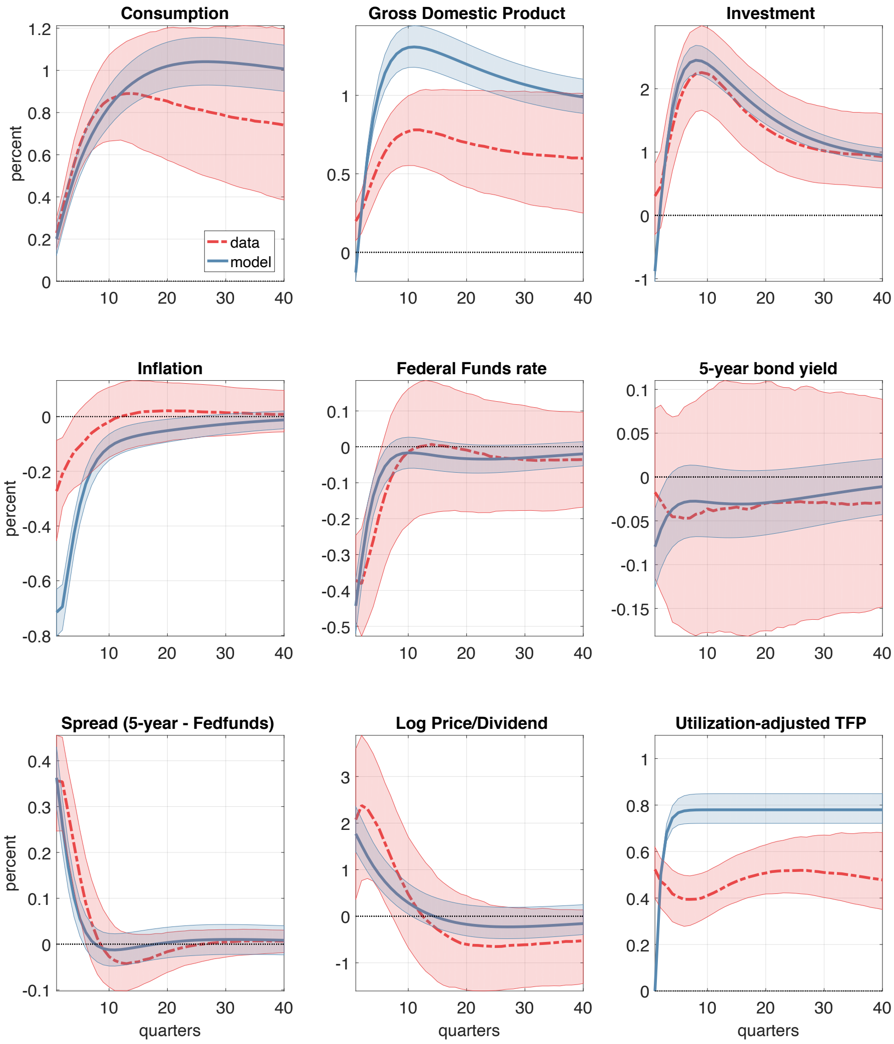
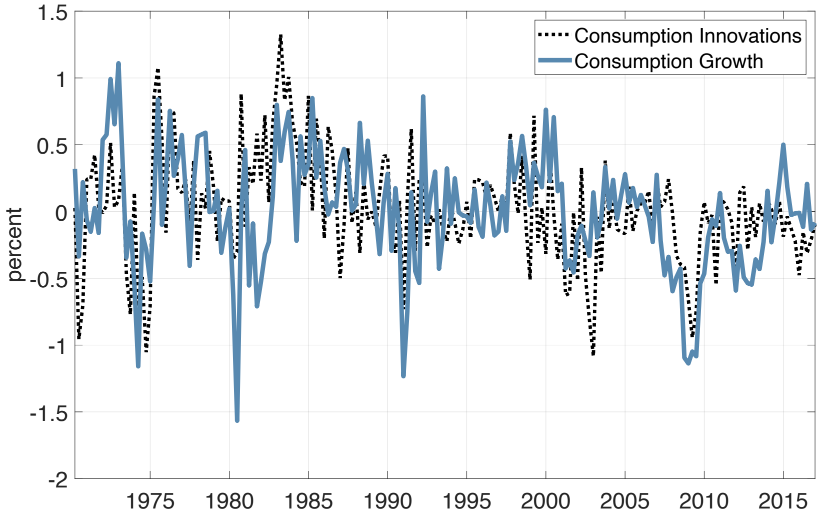
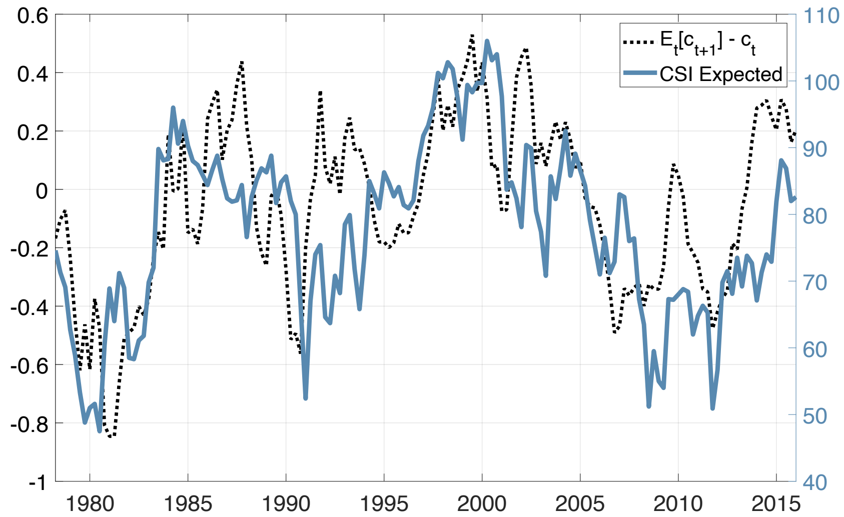


FIGURE 3: **Impulse Responses to News Shocks - Kurmann and Sims (2017) Identification**: This figure plots the impulse response functions of consumption, output, investment, inflation, the Federal Funds rate, 5-year Treasury yield, the slope of the yield curve, the log price-dividend ratio and total factor productivity to a news shock both in the data (red dashed line) and the baseline model (blue solid line). The red and blue shaded areas correspond to 95% confidence bands in the data and the model, respectively. The theoretical IRFs combine the responses to the three news shocks in the model (1Q, 4Q, and 8Q news shocks) by assigning a weight of $\sigma_j^2/(\sigma_{1Q}^2+\sigma_{4Q}^2+\sigma_{8Q}^2)$ to the j-quarter news response. The theoretical responses correspond to 1.2 standard deviation news shocks (for 1Q, 4Q, and 8Q). The shock size is chosen to align the on impact response of the slope of the yield curve (5-year – Fed fund rate) in the data and the model. The empirical impulse responses to a news shock are identified as in Kurmann and Otrok (2017), i.e. without imposing orthogonality to current productivity and maximizing the MFEV objective at the 80 quarter horizon only.

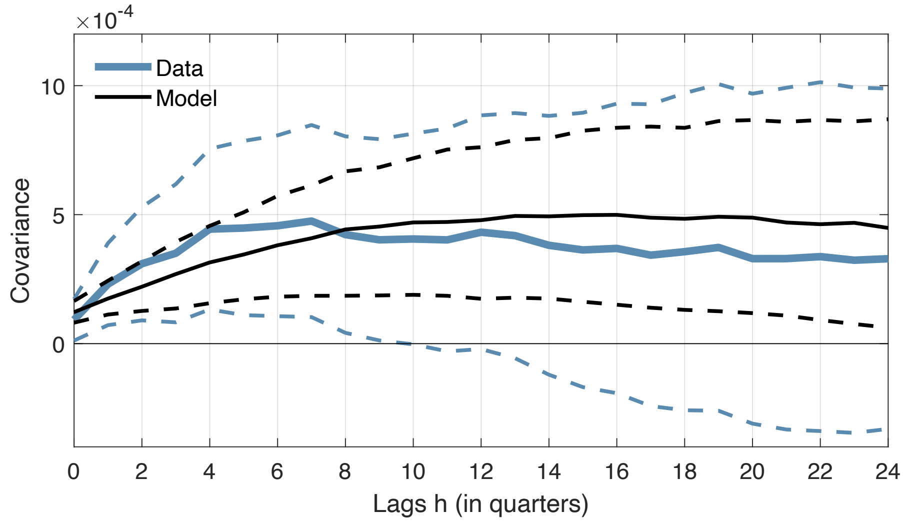


A Consumption Growth and Consumption Innovations.

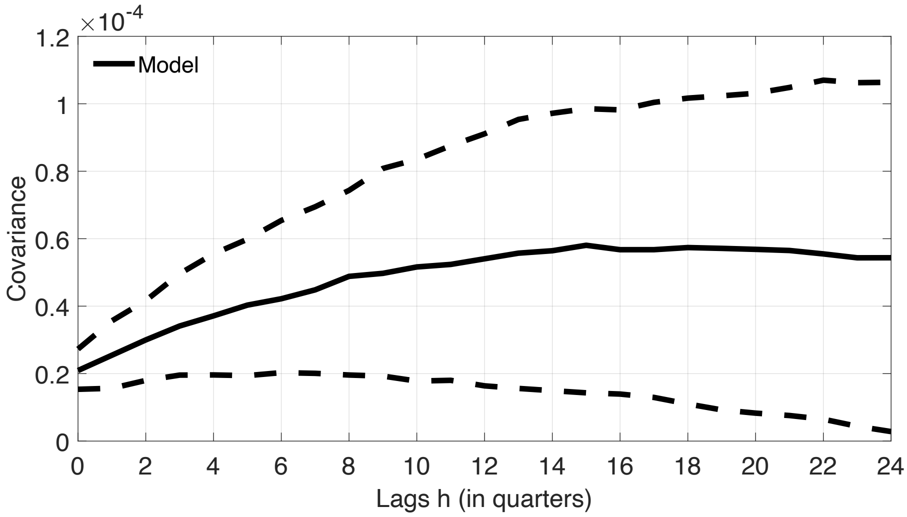


B Expectations and Consumer Sentiment Index.

FIGURE 4: **Consumption and Macroeconomic Expectations**: Panel A of the figure plots the realized consumption growth $c_{t+1} - c_t$ in the data against the estimated consumption innovations $c_{t+1} - \mathrm{E}\left[c_{t+1} \mid \mathcal{I}_t\right]$ that take into account agents' expectations. Panel B plots the difference between the two respective series in Panel A equal to the expected consumption growth $\mathrm{E}\left[c_{t+1} - c_t \mid \mathcal{I}_t\right]$ (left axis) against the University of Michigan Index of Consumer Expectations (right axis). Expected consumption growth series are a four-quarter moving average. The Index of Consumer Expectations data start in January 1978.

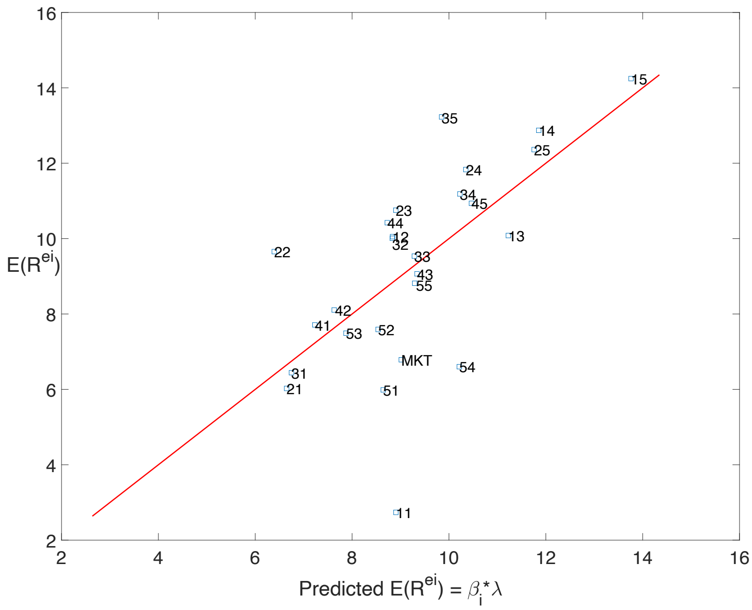


A Covariance of Long-run Consumption Growth and Market Returns.

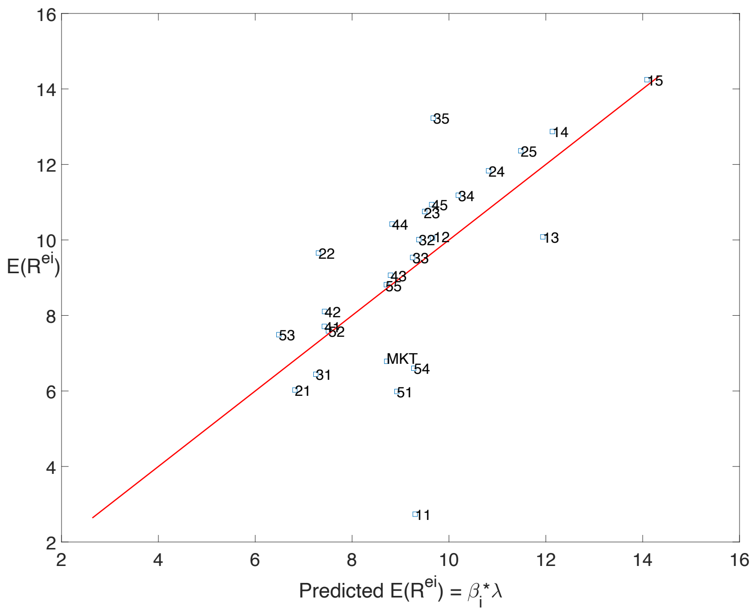


B Covariance of Long-run Consumption Growth and Consumption Innovations.

FIGURE 5: **Consumption Growth Predictability**: Panel A plots the covariance of consumption growth $c_{t+1+h} - c_t$ and aggregate stock market return $r_{t,t+1}$ in the data (thick blue line) and the model (thin black line). The empirical sample consists of quarterly data from 1970:1 to 2016:2. Corresponding model data is obtained from simulating the model 100 times for 185 quarters. The solid lines represent the point estimates of the covariances at different horizons, the dashed lines are 95% confidence bands on Newey-West standard errors. Panel B plots the covariance of consumption growth $c_{t+1+h} - c_t$ and consumption innovations $c_{t+1} - \mathrm{E}[c_{t+1} \mid \mathcal{I}_t]$ in the model.



A SDF innovations.



B Consumption innovations.

FIGURE 6: **Realized vs. Fitted Expected Returns**: The figure shows the pricing errors for each of the 25 Fama-French portfolios for the two one-factor models. In panel A the factor is the innovations in the recursive SDF estimated using the model with news shocks; in panel B the factor is the innovation in consumption estimated using the model with news shocks (where we zeroed monetary shocks). Each two-digit number represents one portfolio. The first digit refers to the size quintiles (1 indicating the smallest firms, 5 the largest), the second digit refers to book-to-market quintiles (1 indicating the portfolio with the lowest book-to-market ratio, 5 with the highest). The pricing errors are from the Fama-MacBeth regressions in Panel A of Table 4 and Table 6.

A Appendix

A.1 Equilibrium conditions

Together with the exogenously given (1), (9), (10), (16)-(17), equilibrium is characterised by the following conditions:

$$V_t = \frac{C_t^{1-1/\psi}}{1-\frac{1}{\psi}} - \eta_0 \frac{A_t^{1-1/\psi} L_t^{1+1/\eta}}{1+\frac{1}{\eta}} + \beta \left[\mathrm{E}_t \left[V_{t+1}^{\gamma} \right] \right]^{\frac{1}{\gamma}},$$

$$\mathrm{E}_t \left[M_{t,t+1} \Pi_{t+1}^{-1} R_{n,t} \right] = 1,$$

$$\mathrm{E}_t \left[M_{t+1} \frac{\Xi_{t+1} \alpha Z_t \left(\frac{A_{t+1} L_{t+1}}{K_{t+1}} \right)^{1-\alpha} + Q_{t+1} \left(1 - \delta + \zeta_1 \left(1 - \zeta \right) \left(\frac{I_{t+1}}{K_{t+1}} \right)^{\zeta} + \zeta_2 \right)}{Q_t} \right] = 1,$$

$$Q_t = \frac{1}{\zeta_1 \zeta} \left[\frac{I_t}{K_t} \right]^{1-\zeta},$$

$$W_t = \Xi_t \left(1 - \alpha \right) Z_t A_t^{1-\alpha} K_t^{\alpha} L_t^{-\alpha},$$

$$\Pi_{o,t} = \frac{\varepsilon}{\varepsilon - 1} \frac{\Phi_{1,t}}{\Phi_{2,t}},$$

$$\Phi_{1,t} = \Pi_t \left[\Xi_t Y_t + \theta \Pi^{-\varepsilon} \mathrm{E}_t \left[M_{t,t+1} \Pi_{t+1}^{\varepsilon-1} \Phi_{1,t+1} \right] \right],$$

$$\Phi_{2,t} = Y_t + \theta \Pi^{1-\varepsilon} \mathrm{E}_t \left[M_{t,t+1} \Pi_{t+1}^{\varepsilon-1} \Phi_{2,t+1} \right],$$

$$\Pi_t^{1-\varepsilon} = \left(1 - \theta \right) \Pi_{o,t}^{1-\varepsilon} + \theta \Pi^{1-\varepsilon},$$

$$\Delta_t = \Pi_t^{\varepsilon} \left[\left(1 - \theta \right) \Pi_{o,t}^{-\varepsilon} + \theta \Pi^{-\varepsilon} \Delta_{t-1} \right],$$

$$\Delta_t Y_t = Z_t \left(A_t L_t \right)^{1-\alpha} K_t^{\alpha},$$

$$Y_t = C_t + I_t.$$

In addition, prices $B_{\tau,t}$ of maturity-τ zero-coupon bonds (with $B_{0,t} = 1$) and the price-to-dividend ratio PD_t are determined, respectively, by the following recursions:

$$B_{\tau,t} = \mathrm{E}_t \left[M_{t,t+1} \Pi_{t+1}^{-1} B_{\tau-1,t+1} \right],$$

$$PD_t = \mathrm{E}_t \left[M_{t,t+1} \frac{D_{t+1}}{D_t} \left[PD_{t+1} + 1 \right] \right].$$

Equation (1) is a shorthand representation of a first order autoregressive system. For simplicity of the presentation, consider the case with four-quarter news only:

$$\Delta \ln A_t = \left(1 - \rho \right) \mu + \rho \Delta \ln A_{t-1} + \varepsilon_{4,t-4}$$

can be rewritten as

$$\begin{bmatrix} \Delta \ln A_t \\ x_{41,t} \\ x_{42,t} \\ x_{43,t} \\ x_{44,t} \end{bmatrix} = \begin{bmatrix} (1-\rho)\mu \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} \rho & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta \ln A_{t-1} \\ x_{41,t-1} \\ x_{42,t-1} \\ x_{43,t-1} \\ x_{44,t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \varepsilon_{4,t}.$$

Moreover, agents' filtration implied by equation (1) has an equivalent noisy signal representation. For simplicity of the presentation, consider the case with one-quarter news only:

$$\Delta \ln A_t = (1-\rho)\mu + \rho \Delta \ln A_{t-1} + \varepsilon_{0,t} + \varepsilon_{1,t-1}.$$

The equivalent representation is given by

$$\Delta \ln A_t = (1-\rho)\mu + \rho \Delta \ln A_{t-1} + \xi_t,$$

$$s_{1,t-1} = \xi_t + \nu_{1,t-1},$$

where

$$\xi_t = \varepsilon_{0,t} + \varepsilon_{1,t-1},$$

$$\nu_{1,t-1} = \left(\kappa^{-1} - 1\right) \varepsilon_{1,t-1} - \varepsilon_{0,t},$$

and $\kappa = \frac{\sigma_\xi^2}{\sigma_\xi^2 + \sigma_\nu^2} = \frac{\sigma_1^2}{\sigma_0^2 + \sigma_1^2}$ is a Kalman gain parameter. Thus, at date $t-1$ agents receive a signal

$$s_{1,t-1} = \kappa^{-1} \varepsilon_{1,t-1}$$

and update their beliefs in line with their beliefs under the news shock representation:

$$\mathrm{E}_{t-1}[\xi_t] = \kappa s_{t-1} = \varepsilon_{1,t-1},$$

$$\mathrm{Var}_{t-1}[\xi_t] = \kappa \sigma_\nu^2 = \sigma_0^2.$$

The general proof is available in Chahrour and Jurado (2018).

A.2 Data used in Model Estimation

Our data sample is from 1970:Q1 to 2016:Q4. Similar to Fernández-Villaverde et al. (2015) we rely on the following macro series from the FRED database of the Federal Reserve of St. Louis:

1. Output is real GDP (GDPC96).
2. Consumption is real personal consumption expenditures (PCECC96).
3. Investment is real gross private domestic investment (GPDIC96).

4. The hourly wage is compensation per hour in the business sector (HCOMPBS) divided by the GDP deflator (GDPDEF).

5. Inflation is based on the GDP deflator (GDPDEF).

The Treasury yield data are from Gurkaynak et al. (2007) (data are available for download on the website `http://www.federalreserve.gov/Pubs/feds/2006/200628/feds200628.xls`), the price-dividend ratio are calculated from data on the CRSP index (NYSE/AMEX /Nasdaq stocks) with and without dividends, and the real stock returns are measured using the Shiller's S&P500 composite index deflated by the CPI index.

A.3 Model Parameters and Moments

The values of the calibrated and estimated parameters are reported in Panels A and B of Table 1, respectively. In particular, we calibrate $\delta = 0.03$, $\alpha = 0.36$ and $\chi = 3$, in line with standard calibrations for the U.S. economy. We follow Barsky et al. (2015) and calibrate price rigidity and wage inertia parameters to $\theta = 0.76$ and $\rho_w = 0.9$, respectively. As argued by these authors, wage inertia limits wage growth in response to anticipated increases in productivity. This helps the model to match the low inflation and the progressive increase in investment after a positive news shock. The monetary policy rule is characterized by the parameters $\Pi = 1.008$, $\rho_r = 0.7$, $\phi_\pi = 1.5$, $\phi_{y1} = 0.7$, and $\phi_{y2} = 0.08$. The calibration puts more weight on the output growth relative to the output gap, in line with the rule embedded in the Federal Reserve Bank of New York DSGE model, see Del Negro et al. (2013), and the intuition that, in practice, the monetary authority reacts to more readily observed variables.

Panel B reports our estimated parameters. Our estimate for the elasticity of intertemporal substitution $\psi = 1.65$ is greater than one, in line with the values used in the long-run risk literature (see, e.g., Bansal and Yaron, 2004; Kaltenbrunner and Lochstoer, 2010; Croce, 2014). With a high EIS, agents respond to expected productivity improvements with only small immediate increases in consumption. If instead the elasticity were low, agents would have immediately adjusted their consumption to anticipated increases in productivity, resulting in counterfactually low or even negative correlation between asset valuations and subsequent growth in output, consumption, and investment. While a large fraction of future productivity growth is anticipated up to eight quarters ahead, this growth is not necessarily very persistent, as indicated by the estimated value of $\rho_a = 0.36$. This is in contrast with the long-run risk literature (see, e.g., Bansal and Yaron, 2004), where the predictable component of economic fundamentals is small and highly persistent.

Table 2 reports the moments generated by the model and compares them to the data. For model moments, we report the median and the 90 percent probability intervals that account for parameter uncertainty. Overall the model does a good job at matching data counterparts. In particular, the model reproduces the volatility of consumption and investment, on the macro side, and that of the short rate and term structure slope, on the financial side. The table also shows moments that are not targeted in the estimation. Interestingly, the model matches well the average level and the persistence of yield on real 2-year, and nominal 10-year bonds.

Within the model, there is a trade off between inflation and yield variability: lowering inflation variability induces too low yield volatilities, in particular, for longer term maturities. Another well known challenge is matching the volatility of the price-to-dividend ratio which is between 41% and 73% of that in the data. However, these numbers represent no small accomplishment, since most models need stochastic volatility to generate volatile prices. E.g. Bansal and Yaron (2004) generate volatile prices and returns in an endowment economy with time-varying volatility in consumption. In contrast, production economy featuring long-run productivity risk but no stochastic volatility generate returns that are less volatile than those observed in the data, see, for instance, Croce (2014). In addition, by matching the unconditional means of the price-to-dividend ratio and the slope of the term structure, the model also generates a sizable equity risk premium, a moment that is not targeted in the estimation.

Finally, our economy also reproduces well the empirical autocorrelation functions of several macro and financial variables, as reported in Figure 1. For example, the model captures the full extent of the persistence of inflation and nominal interest rates.

A.4 VAR Analysis: Data and Identification

The data series for the VAR analysis in Figure 2 are by and large similar to those used in the larger VAR specifications in Kurmann and Otrok (2013). Consumption is measured as the log of real chain-weighted total personal consumption expenditures adjusted for population growth. Inflation is measured by the growth rate in the GDP deflator. The slope is measured as the spread between the five-year zero coupon yield and the Federal Funds rate. The long bond yield is computed as the sum of the spread and the Federal Funds rate. We also use real gross private domestic investment, real GDP, and the price-dividend ratio. Very similar results are obtained by replacing the dividend-price ratio with the Shiller's S&P500 composite index, deflated by CPI index.

The VAR is estimated for the 1959:2–2016:4 sample. In keeping with the standard practice in the literature, the VAR is estimated with 4 lags subject to a Minnesota prior.

Following Barsky and Sims (2011), the news shock is identified as the innovation that accounts for the maximum forecast error variance share (MFEV) of productivity over a given forecast horizon, but with the additional restriction that the innovation is orthogonal to current productivity. This is a partial identification approach that does not require us taking a stand on the nature of non-news shocks. We rely on a partial identification since full identification approaches like Beaudry and Portier (2006) and Beaudry and Lucke (2010) are potentially subject to robustness issues (see Kurmann and Mertens (2014) and Fisher (2010) a discussion). Specifically, we follow Kurmann and Otrok (2017) and include forecast horizons between 0 and 80 quarters in the MFEV objective. Since the forecast error variance is a squared object, an additional rotation condition is needed to sign the shock. As discussed in Kurmann and Otrok (2017) one needs to be careful with imposing the rotation condition at too short of a horizon if the response of productivity to a news shock is delayed as is argued for example by Beaudry and Portier (2006) or if the response is surrounded by substantial uncertainty. See also Cascaldi-Garcia (2017). We therefore impose the rotation condition at 40 quarters, although none of the results would change if we imposed the rotation condition at 20 quarters.

The assumption that news shocks are orthogonal to current TFP is consistent with our fully-specified DSGE model, where we assume that news affect technology (and other exogenous states variables) only with a lag. This identifying assumption has been recently challenged by Barsky, Basu, and Lee (2015, p. 232): "It is possible that news about future productivity arrives along with innovations in productivity today." To this end we also consider an alternative identification of news shocks proposed by Kurmann and Sims (2017). This identification scheme does not impose contemporaneous orthogonality with productivity and applies the MFEV objective at the 80-quarter horizon.

Figure 3 and show the results obtained by employing the Kurmann and Sims (2017) identification. The main difference between the empirical responses in Figure 2 and Figure 3 lies in the response of adjusted TFP which reacts on impact when news shocks are identified as in

Kurmann and Sims (2017). Interestingly, this response of adjusted TFP is closer to the model-implied response than it was the case in Figure 2. All other impulse responses are very much robust and essentially the same as in Figure 2.

A.5 Model-implied Impulse Response Functions

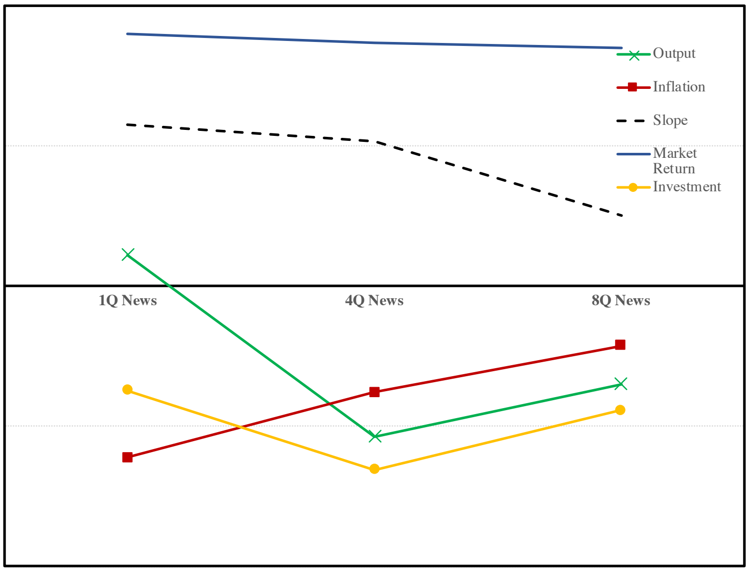
The calculation of model-implied impulse response functions follows closely the methodology of Fernández-Villaverde et al. (2015) and we proceed as follows:

1. We simulate the model for 3000 quarters, starting at the deterministic steady state and assuming that there are no structural shocks hitting the system. In our setup, the endogenous model variables converge after roughly 1000 quarters to their ergodic mean in absence of shocks (EMAS).
2. In a next step, we start simulating from the EMAS directly. We add a shock of interest and iterate the system forward for 40 periods.
3. The impulse response functions are defined as the difference between the path from step 2 and the EMAS.
4. Finally, we repeat the above steps 200 times solving our model for 200 draws of parameters to account for parameter uncertainty.

A heuristic analysis of our calculated impulse response functions at various orders of approximations shows that the responses are effectively identical to the generalized impulse response functions proposed by Koop et al. (1996). This also means that starting at the ergodic mean in absence of shocks rather than at the true analytical ergodic mean does not affect the results in this specific model environment.

A.6 Model Restrictions

In this section, we report the coefficients of first-order optimal policy rules that determine the reaction of the model variables used in the estimation to news shocks with different horizon. Keeping the shock sizes constant, different variables load differently on news with different horizon, as shown on the figure below, helping the identification of news at different horizons using contemporaneous covariances between the variables.



In particular, the stock market response to news at different horizons is almost identical across horizons as expected permanent productivity gains are immediately impounded in the stock prices. The different adjustment speeds of macro aggregates lead to more complex patterns for the other variables, including output, interest rates, and inflation. For instance, the non-monotonicity of output and investment coefficients results from the relative strength of agent's desire to smooth consumption and her desire to smooth investment (under various rigidities) in anticipation of higher productivity at different horizons.

A.7 First-Pass Estimates of Betas

We compute first-pass estimates of the betas by running the least squares regressions:

$$R_{it}^{e} = a_i + \beta_{i,f} f_t + \varepsilon_{i,t} \ , \ t = 1, \ldots, T, \quad \text{for each } i = 1, \ldots, n$$

where f_t is the risk factor. When there is spread in the expected returns across portfolios, there should also be statistically significant spread in the betas across portfolios. With this in mind, we test whether for each factor (consumption or SDF) filtered from our news model, the factor betas are jointly significantly different from a constant. We compute standard errors using a GMM-based procedure.

For the 25 Fama-French book-to-market and size portfolios, the table below indicates that, at conventional significance levels, one can reject the hypotheses that $\beta_{ij} = \beta_j, \forall i$.

Tests for no spread (p-values)

Consumption	**SDF**
0.000	**0.000**

For the components of market-to-book, the table below shows that we can reject the hypothesis that $\beta_H = \beta_L$ (i.e., absence of spread in the betas between the extreme portfolios) for the firm-specific error. In contrast, we cannot reject the null of a statistically insignificant spread for sector error and the value-to-book.

Tests for no spread (p-values)		
	Consumption	**SDF**
Market-to-value (firm-specific error)	**0.062**	**0.066**
Market-to-value (sector error)	0.164	0.117
Value-to-book	0.320	0.465

A.8 Additional results for the 25 Fama-French Portfolios

Table A.2 shows that our results in Panel A of Table 4 continue to hold when we consider the sub-sample going from 1982 to 2016. In particular, the magnitude and significance of the premia on the consumption and SDF innovations implied by our news model are by and large similar to what is reported in Table 4 for the full sample. The sample split in 1982:Q3 is motivated by Gambetti, Korobilis, Tsoukalas and Zanetti (2017) who show that the response of short- and long-term interest rates to news in TFP is affected by the stance of monetary policy which was restrictive before the 1980s and neutral/accommodative in the post-1980 period. Gambetti et al. (2017) also suggest to remove the period 1979:Q3-1982:Q2 because of unusual operating procedures that were effective during that episode.

Next we follow Kan, Robotti and Shanken (2013) and we add five industry portfolios to the 25 size and book-to-market portfolios of Fama and French (1992) as the test assets. The industry portfolios are included to provide a greater challenge to the various asset pricing models, as recommended by Lewellen, Nagel and Shanken (2010). Table A.3 reports corresponding results for the model-implied SDF and the unrestricted news shocks. In short, the results confirm that the excellent pricing ability of our news-driven SDF is not impaired by the larger cross-section of equities. For instance, the R^2 decreases only slightly from 40% (see Panel A in Table 4) to 38%, and the root mean squared errors (RMSE) and mean absolute pricing errors (MAPE) remain mostly unchanged (from 2.02% and 1.49% to 1.98% and 1.51%).

A.9 Additional results for the Bond and Stock Portfolios

This table reports pricing errors on the 5 book-to-market sorted stock portfolios, the value-weighted market portfolio, and six bond portfolios of maturities 1-2, 2-3, 3-4, 4-5, 5-10, and more than 10 years. They are expressed in percent per year (quarterly numbers multiplied by 400). Each column corresponds to a different stochastic discount factor (SDF) model. The first column contains the risk-neutral SDF and therefore reports the average pricing errors to be explained. The second column has the SDF as the only factor. The third column presents results for our the SDF when only the fundamental (i.e. ultimately realized) component of news is active. The fourth column presents the results for our SDF when only the pure belief component of news is active. The sample is Jun 1970 through December 2017.

	(1) SDF Risk Neutral	(2) SDF	(3) SDF funda.	(4) SDF beliefs
Bonds				
1-2 yr	-4.18	-1.89	-1.12	-4.76
2-3 yr	-3.72	-1.05	-0.57	-3.70
3-4 yr	-3.32	-0.32	-0.09	-2.70
4-5 yr	-3.20	0.17	0.15	-1.96
5-10 yr	-2.75	0.65	0.38	-0.98
>10 yr	-1.57	1.66	1.24	1.28
Market	1.89	-0.78	-1.56	2.07
Book-to-Market				
Growth	1.03	-0.89	-2.42	1.97
Value	6.29	0.97	2.37	2.17
MAPE Bond	3.124	0.956	0.592	2.565
MAPE V-G	3.663	0.933	2.396	2.070

A.10 Additional results for Book-to-Market decomposition

Table A.4 reports the performance of our model-implied SDF when confronted with the simple decomposition of market-to-book proposed by Golubov and Konstantinidi (2019). In short, the table shows that the association between our SDF and the market-to-book (Panel A) derives from the market-to-value (Panel B) and not from the unpriced value-to-book (Panel C) component.

It is also comforting that when we use 10 portfolios sorted on market-to-book in Panel A of Table A.4 we find very similar results (e.g., the premium for the model-implied SDF stays basically unchanged not only in terms of significance but also in terms of magnitude) to those in Table 4-Panel A where we were using 25 portfolios formed on size and market-to-book. This is not a trivial result: indeed, Phalippou (2007) shows that a minor alteration of the test assets can lead to a dramatically different answer regarding the validity of a given asset pricing model.

More interestingly, when we use the noise component of news to construct our SDF factor we observe the performance of the model in explaining the market-to-value portfolios improves. Specifically, moving from specification in row one to row three in Panel B we note that the R^2 raises from 0.28 to 0.39 for the SDF. In turn, the variability of the R^2 decreases.

A.11 Additional Tables

TABLE A.1: **Unconditional C-CAPM and CAPM.** The table reports results of the cross-sectional regression

$$\overline{R_i^e} = \lambda_0 + \beta_i \lambda + \alpha_i,$$

where $\overline{R_i^e}$ is the mean excess return of portfolio i and β_i is the vector of factor betas of portfolio i estimated in the first-pass regression. The models are estimated using quarterly excess returns on the 25 Fama-French size and book-to-market ranked portfolios. The table reports the estimates of the factor risk premia $\widehat{\lambda}$ and the constant term, Fama and MacBeth (1973) standard errors (in parentheses), and the GMM-VARHAC standard errors (accounting for the sampling error in the betas) for these estimates (in braces). The second to last column reports asymptotic p-values of chi-squared tests of the null hypothesis that all pricing errors are jointly zero (Joint p-value). To compute the test statistic we use the OLS covariance matrix of $\widehat{\alpha}$. The last column reports the R^2 of the cross-sectional regression and its standard error (under the assumption that $0 < R^2 < 1$). We report in bold font values that are significant at the 10% level. We also report the root mean square alpha (RMSE) and the mean absolute pricing error (MAE) across all test assets. These are expressed as percentages per year. The data are quarterly from March 1970 through December 2016.

Constant	λ_{CG}	λ_{MKT}	RMSE	MAPE	Joint p-value	R^2
0.034		-0.010	2.501	2.125	0.000	0.08
(0.011)		(0.012)				(0.19)
{0.011}		{0.012}				
0.025	-0.000		2.604	2.141	0.000	0.00
(0.007)	(0.002)					(0.06)
{0.008}	{0.002}					
0.034	0.003	-0.010	2.413	1.989	0.000	0.14
(0.011)	(0.002)	(0.012)				(0.39)
{0.012}	{0.003}	{0.013}				

TABLE A.2: **Robustness to Sample Period.** The table reports results of the cross-sectional regression

$$\overline{R_i^e} = \lambda_0 + \beta_i \lambda + \alpha_i,$$

where $\overline{R_i^e}$ is the mean excess return of portfolio i and β_i is the factor beta of portfolio i estimated in the first-pass regression. The models are estimated using quarterly excess returns on the 25 Fama-French size and book-to-market ranked portfolios. The table reports the estimates of the factor risk premia $\widehat{\lambda}$ and the constant term, Fama and MacBeth (1973) standard errors (in parentheses), and the GMM-VARHAC standard errors (accounting for the sampling error in the betas) for these estimates (in braces). The second to last column reports asymptotic p-values of chi-squared tests of the null hypothesis that all pricing errors are jointly zero (Joint p-value). To compute the test statistic we use the OLS covariance matrix of $\widehat{\alpha}$. The last column reports the R^2 of the cross-sectional regression and its standard error (under the assumption that $0 < R^2 < 1$). We report in bold font values that are significant at the 10% level. We also report the root mean square alpha (RMSE) and the mean absolute pricing error (MAE) across all test assets. These are expressed as percentages per year. The data are quarterly from September 1982 through December 2016 as in Gambetti, Korobilis, Tsoukalas and Zanetti (2017).

Constant	λ_C	λ_{SDF}	RMSE	MAPE	Joint p-value	R^2
0.024	**0.002**		2.148	1.531	0.000	0.27
(0.008)	(0.001)					(0.22)
{0.010}	{0.001}					
0.024		**-0.370**	2.125	1.508	0.000	0.29
(0.008)		(0.143)				(0.22)
{0.010}		{0.162}				

TABLE A.3: **Robustness to Industry Portfolios.** The table reports results of the cross-sectional regression

$$\overline{R_i^e} = \lambda_0 + \beta_i \lambda + \alpha_i,$$

where $\overline{R_i^e}$ is the mean excess return of portfolio i and β_i is the factor beta of portfolio i estimated in the first-pass regression. The models are estimated using quarterly excess returns on the 25 Fama-French size and book-to-market ranked portfolios and five industry portfolios. The table reports the estimates of the factor risk premia $\widehat{\lambda}$ and the constant term, Fama and MacBeth (1973) standard errors (in parentheses), and the GMM-VARHAC standard errors (accounting for the sampling error in the betas) for these estimates (in braces). The second to last column reports asymptotic p-values of chi-squared tests of the null hypothesis that all pricing errors are jointly zero (Joint p-value). To compute the test statistic we use the OLS covariance matrix of $\widehat{\alpha}$. The last column reports the R^2 of the cross-sectional regression and its standard error (under the assumption that $0 < R^2 < 1$). We report in bold font values that are significant at the 10% level. We also report the root mean square alpha (RMSE) and the mean absolute pricing error (MAE) across all test assets. These are expressed as percentages per year. The data are quarterly from September 1970 through December 2016.

Constant	λ_C	λ_{SDF}	RMSE	MAPE	Joint p-value	R^2
0.006	**0.003**		1.896	1.427	0.000	0.41
(0.008)	(0.001)					(0.29)
{0.012}	{0.001}					
0.015		**-0.458**	1.977	1.514	0.000	0.38
(0.008)		(0.166)				(0.22)
{0.011}		{0.256}				

TABLE A.4: **Components of the Market-to-Book – Simple Decomposition.** The table reports results of the cross-sectional regression

$$\overline{R_i^e} = \lambda_0 + \beta_i \lambda_{SDF} + \alpha_i,$$

where $\overline{R_i^e}$ is the mean excess return of portfolio i and β_i is the factor beta of portfolio i estimated in the first-pass regression. In Panel A we use quarterly excess returns on 10 market-to-book ranked portfolios. In Panel B we use quarterly excess returns on 10 market-to-value (total error) ranked portfolios. In Panel C we use quarterly excess returns on 10 value-to-book ranked portfolios. Data on portfolios in all Panels are from Golubov and Konstantinidi (2019). The table reports the estimates of the factor risk premia $\widehat{\lambda}$ and the constant term, Fama and MacBeth (1973) standard errors (in parentheses), and the GMM-VARHAC standard errors (accounting for the sampling error in the betas) for these estimates (in braces). The second to last column reports asymptotic p-values of chi-squared tests of the null hypothesis that all pricing errors are jointly zero (Joint p-value). To compute the test statistic we use the OLS covariance matrix of $\widehat{\alpha}$. The last column reports the R^2 of the cross-sectional regression and its standard error (under the assumption that $0 < R^2 < 1$). We report in bold font values that are significant at the 10% level. We also report the root mean square alpha (RMSE) and the mean absolute pricing error (MAE) across all test assets. These are expressed as percentages per year. The data are quarterly from March 1970 through June 2013.

Constant	(1) λ_{SDF}	(2) λ_{SDF} funda.	(3) λ_{SDF} beliefs	RMSE	MAPE	Joint p-value	R^2
		Panel A: Market-to-book					
0.027	**-0.585**			2.074	1.368	0.003	0.42
(0.010)	(0.261)						(0.45)
{0.015}	{0.345}						
-0.004		-0.597		2.238	1.780	0.007	0.33
(0.012)		(0.209)					(0.19)
{0.046}		{0.905}					
0.032			**-0.351**	2.097	1.321	0.004	0.41
(0.010)			(0.157)				(0.36)
{0.011}			{0.192}				
		Panel B: Market-to-value (total error)					
0.025	**-0.670**			2.458	1.862	0.000	0.28
(0.010)	(0.274)						(0.51)
{0.016}	{0.405}						
0.034		**0.169**		2.851	2.445	0.000	0.03
(0.008)		(0.078)					(0.39)
{0.009}		{0.091}					
0.032			**-0.463**	2.270	1.758	0.000	0.39
(0.011)			(0.169)				(0.41)
{0.014}			{0.248}				
		Panel C: Value-to-book					
0.026	-0.151			0.685	0.561	0.391	0.10
(0.010)	(0.386)						(0.53)
{0.010}	{0.454}						
0.021		-0.108		0.625	0.492	0.380	0.25
(0.015)		(0.167)					(0.89)
{0.018}		{0.198}					
0.028			-0.073	0.709	0.569	0.350	0.04
(0.009)			(0.298)				(0.31)
{0.010}			{0.332}				

TABLE A.5: **Components of the Market-to-Book – Consumption Risk.** The table reports results of the cross-sectional regression

$$\overline{R_i^e} = \lambda_0 + \beta_i \lambda_C + \alpha_i,$$

where $\overline{R_i^e}$ is the mean excess return of portfolio i and β_i is the factor beta of portfolio i estimated in the first-pass regression. In Panel A we use quarterly excess returns on 10 market-to-value (firm-specific error) ranked portfolios. In Panel B we use quarterly excess returns on 10 market-to-value (sector error) ranked portfolios. In Panel C we use quarterly excess returns on 10 value-to-book ranked portfolios. Data on portfolios in all Panels are from Golubov and Konstantinidi (2019). The table reports the estimates of the factor risk premia $\widehat{\lambda}$ and the constant term, Fama and MacBeth (1973) standard errors (in parentheses), and the GMM-VARHAC standard errors (accounting for the sampling error in the betas) for these estimates (in braces). The second to last column reports asymptotic p-values of chi-squared tests of the null hypothesis that all pricing errors are jointly zero (Joint p-value). To compute the test statistic we use the OLS covariance matrix of $\widehat{\alpha}$. The last column reports the R^2 of the cross-sectional regression and its standard error (under the assumption that $0 < R^2 < 1$). We report in bold font values that are significant at the 10% level. We also report the root mean square alpha (RMSE) and the mean absolute pricing error (MAE) across all test assets. These are expressed as percentages per year. The data are quarterly from March 1970 through June 2013.

Constant	(1) λ_C	(2) λ_C funda.	(3) λ_C beliefs	RMSE	MAPE	Joint p-value	R^2
		Panel A: Market-to-value (firm-specific error)					
0.020	**0.005**			2.049	1.471	0.001	0.52
(0.009)	(0.001)						(0.36)
{0.017}	{0.002}						
-0.000		0.002		2.756	2.242	0.001	0.14
(0.012)		(0.001)					(0.49)
(0.021)		(0.003)					
0.028			**0.003**	1.873	1.488	0.001	0.60
(0.010)			(0.001)				(0.29)
{0.011}			{0.001}				
		Panel B: Market-to-value (sector error)					
0.028	-0.001			0.878	0.709	0.502	0.19
(0.010)	(0.001)						(0.63)
{0.010}	{0.001}						
0.022		0.000		0.961	0.743	0.551	0.03
(0.020)		(0.001)					(0.36)
{0.022}		{0.001}					
0.026			-0.000	0.966	0.761	0.498	0.02
(0.009)			(0.173)				(0.21)
{0.010}			{0.203}				
		Panel C: Value-to-book					
0.024	0.001			0.624	0.556	0.455	0.26
(0.011)	(0.002)						(0.88)
{0.012}	{0.003}						
0.014		0.001		0.506	0.346	0.443	0.51
(0.018)		(0.001)					(0.75)
{0.022}		{0.001}					
0.027			0.001	0.651	0.580	0.400	0.19
(0.009)			(0.002)				(0.76)
{0.010}			{0.002}				

TABLE A.6: **News Horizon.** The table reports results of the cross-sectional regression

$$\overline{R_i^e} = \lambda_0 + \beta_i \lambda + \alpha_i,$$

where $\overline{R_i^e}$ is the mean excess return of portfolio i and β_i is the vector of factor betas of portfolio i estimated in the first-pass regression. In Panel A the models are estimated using the models are estimated using quarterly excess returns on the 25 Fama-French size and book-to-market ranked portfolios. In Panel B the models are estimated using five book-to-market sorted quintile stock portfolios, the value-weighted market portfolio, and six maturity-sorted Fama bond portfolios obtained from the Center for Research in Security Prices Treasury. In Panel C the models are estimated using quarterly excess returns on the ten portfolios sorted on cash flow duration from Weber (2018). The table reports the estimates of the factor risk premia $\widehat{\lambda}$ and the constant term, Fama and MacBeth (1973) standard errors (in parentheses), and the GMM-VARHAC standard errors (accounting for the sampling error in the betas) for these estimates (in braces). The second to last column reports asymptotic p-values of chi-squared tests of the null hypothesis that all pricing errors are jointly zero (Joint p-value). To compute the test statistic we use the OLS covariance matrix of $\widehat{\alpha}$. The last column reports the R^2 of the cross-sectional regression and its standard error (under the assumption that $0 < R^2 < 1$). We report in bold font values that are significant at the 10% level. We also report the root mean square alpha (RMSE) and the mean absolute pricing error (MAE) across all test assets. These are expressed as percentages per year. The data are quarterly from March 1970 through December 2016.

Constant	λ_{1Q}	λ_{4Q}	λ_{8Q}	RMSE	MAPE	Joint p-value	R^2
		Panel A: Book-to-Market and Size Portfolios					
0.014	**0.299**	0.187	**0.162**	1.804	1.379	0.000	0.52
(0.007)	(0.113)	(0.135)	(0.063)				(0.22)
{0.012}	{0.116}	{0.159}	{0.074}				
		Panel B: Bond and Stock Portfolios					
0.008	**0.851**	0.854	0.163	1.117	0.910	0.005	0.89
(0.003)	(0.392)	(0.463)	(0.106)				(0.12)
{0.007}	{0.457}	{1.196}	{0.271}				
		Panel C: Duration Portfolios					
0.054	**0.543**	0.298	**0.213**	1.079	0.953	0.000	0.92
(0.010)	(0.125)	(0.121)	(0.058)				(0.07)
{0.019}	{0.219}	{0.211}	{0.102}				

TABLE A.7: **Model Reestimated without News Shocks.** The table reports results of the cross-sectional regression

$$\overline{R_i^e} = \lambda_0 + \beta_i \lambda + \alpha_i,$$

where $\overline{R_i^e}$ is the mean excess return of portfolio i and β_i is the factor beta of portfolio i estimated in the first-pass regression. The models are estimated using quarterly excess returns on the 25 Fama-French size and book-to-market ranked portfolios. The table reports the estimates of the factor risk premia $\widehat{\lambda}$ and the constant term, Fama and MacBeth (1973) standard errors (in parentheses), and the GMM-VARHAC standard errors (accounting for the sampling error in the betas) for these estimates (in braces). The second to last column reports asymptotic p-values of chi-squared tests of the null hypothesis that all pricing errors are jointly zero (Joint p-value). To compute the test statistic we use the OLS covariance matrix of $\widehat{\alpha}$. The last column reports the R^2 of the cross-sectional regression and its standard error (under the assumption that $0 < R^2 < 1$). We report in bold font values that are significant at the 10% level. We also report the root mean square alpha (RMSE) and the mean absolute pricing error (MAE) across all test assets. These are expressed as percentages per year. The data are quarterly from March 1970 through December 2016.

Constant	λ_C	λ_{SDF}	RMSE	MAPE	Joint p-value	R^2
0.008	0.003		2.099	1.498	0.000	0.35
(0.007)	(0.001)					(0.34)
{0.013}	{0.002}					
0.019		**-0.220**	2.277	1.809	0.000	0.23
(0.008)		(0.090)				(0.33)
{0.010}		{0.112}				