

# News Shocks and Asset Prices

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January 27, 2019

## Abstract

We examine the role of expectation, or news, shocks for the measurement of macroeconomic risk and the natural rate of interest. To this end, we estimate a New-Keynesian dynamic stochastic general equilibrium model that allows us to infer agents' expectations about future fundamentals at different horizons. Accounting for news shocks results in better-specified macroeconomic risk factors that have significant explanatory power for the cross-section of stock and long-term bond returns. Further, anticipated changes in future productivity growth induce sizable fluctuations in the natural rate of interest, which we show to have important implications for the conduct of monetary policy.

**Keywords:** News Shocks, Consumption-CAPM, Natural Rate of Interest

**JEL Classification:** G12, E32, E21, C63

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The views expressed here are our own and do not reflect those of the Federal Reserve Board of Governors. We are grateful to Elena Afanasyeva, Michael Kiley, Franck Portier and seminar participants at the Federal Reserve Board, the Warwick Business School, Queen Mary University, the Bank for International Settlements, and the 13th Swiss Economists Abroad Conference for valuable comments.

# 1 Introduction

The view that economic fluctuations are driven by changes in agents' expectations has a long history and, in recent years, it has been formalized by the literature on news shocks.<sup>1</sup> In the expectation-driven business cycle paradigm, agents decide to consume or invest in capital and financial assets based on information that cannot be trivially inferred from the history of fundamentals. In this paper we explore the qualitative and quantitative implications of accounting for this latent information for the natural rate of interest and the measurement of macroeconomic risk.

Our contribution is threefold. First, we infer agents' expectations about future fundamentals at different horizons using an estimated New-Keynesian dynamic stochastic general equilibrium model with news shocks. Second, we show that news shocks are a priced risk factor. In particular, consumption growth innovations measured conditional on news have significant explanatory power for the cross-section of expected stock and long-term bond returns. Finally, we find that fluctuations in expected consumption growth conditional on news contribute to a significant variation in the natural rate of interest at business cycle frequencies. We further show that this time-variation in the natural rate has important implications for the conduct of monetary policy.

To study agents' expectations, we use a standard New-Keynesian model and augment it with news shock, i.e. changes in productivity that are anticipated by agents at different horizons. The model has an equivalent representation in which agents receive noisy signals about future productivity, providing us with an additional intuition for the results.<sup>2</sup> By definition, news are information available to agents that is not yet reflected in the production possibilities of the economy. This makes the identification in the data

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<sup>1</sup>See [Pigou \(1927\)](#) for an early exposition of this view, and the subsequent pioneering work of [Beaudry and Portier \(2004\)](#).

<sup>2</sup>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, “noise” and “news”, are observationally equivalent. In the rest of the paper we take a news perspective.

not trivial. Theoretical restrictions imposed by the structural model on the responses of endogenous variables to news allow us to overcome this challenge. Under the efficient market hypothesis, asset prices can be particularly informative about news; accordingly, we include the slope of the term structure and the aggregate price-to-dividend ratio into our analysis alongside macroeconomic variables.<sup>3</sup>

Our estimated model matches salient macroeconomic and asset pricing moments. Further, model-implied responses of endogenous variables to news shocks mimic those identified in empirical VARs using different identification strategies proposed in the literature. At the same time, our model allows to identify a richer information structure that differentiates between news at different horizons, highlighting the advantage of the structural estimation.

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 quarters ahead remain statistically and economically significant. Combined across all horizons, news about future productivity explain a large fraction of business cycle fluctuations. Finally, using the equivalent representation of our model proposed by [Chahrour and Jurado \(2018\)](#), we find that macroeconomic fluctuations are primarily driven by correctly anticipated changes in future fundamentals. Compared with macroeconomic fluctuations, asset price volatility is to a larger degree due to the variation in pure beliefs.

Having established the importance of news for macro-finance fluctuations, we con-

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<sup>3</sup>The presence of anticipated innovations with multi-period anticipation horizons introduces multiple latent state variables. This proliferation of states makes it less likely that the dynamics of the observables possess a VAR representation. This is known as the invertibility problem (see, e.g. [Lippi and Reichlin, 1994](#); [Leeper et al., 2013](#); [Beaudry and Portier, 2014](#)). As a result, in general, a VAR methodology may not identify the anticipated component of structural shocks. We instead follow the lead of [Schmitt-Grohe and Uribe \(2012\)](#) who show that estimation based on a DSGE model does not suffer from the aforementioned invertibility problem. Finally, [Blanchard et al. \(2013\)](#) show that VAR methods cannot be used to evaluate the effects of noise shocks because of a fundamental non-invertibility problem, and a structural estimation approach is necessary to address this question. See also Section 4.2.3 in [Beaudry and Portier \(2014\)](#) for a discussion of invertibility issues due to signal-extraction problem.

sider their effect on interest rates and risk premia.

First, allowing for news shocks leads to a better identification of macroeconomic risks. Through the lens of our model, news shocks appear to be important drivers of business cycle fluctuations in the price-to-dividend ratio, equity returns, and the predictability of consumption growth by equity returns. We therefore investigate the pricing ability of risk factors implied by our model. Our findings are striking: once we account for the effect of news shocks on expected consumption, innovations in consumption explain a large fraction of cross-sectional differences in the expected returns of the 25 Fama-French size and book-to-market portfolios. This contrasts with the poor results obtained when we use consumption growth or market portfolio returns as risk factors. Importantly, the performance of our model-implied consumption risk factor is not subsumed by that of the ultimate consumption factor proposed by [Parker \(2003\)](#) and [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. Furthermore, our model-implied factors perform well for industry portfolios, stock portfolios sorted on firm cash flow duration, and long-term bonds.<sup>4</sup> Finally, cross-sectional regressions on one-, four-, and eight-quarters news filtered from our model suggest that different assets are informative for different news shock horizons. While long-term bond returns are mainly exposed to one-quarter news, value-growth and duration-sorted equity portfolio also load on long-term eight-quarters news. We conclude that distinguishing news by their anticipation horizon is important for the purpose of asset pricing.

Next, we find that news-induced variation in expected consumption induce sizable fluctuations in the natural rate of interest, defined as the real short rate that would have

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<sup>4</sup>[Bryzgalova and Julliard \(2018\)](#) show that aggregate consumption growth reacts slowly to common innovations in bond and stock returns. Such a behavior is consistent with news shocks and the economic mechanism of our model.

prevailed in the absence of nominal rigidities. Motivated by this finding, we use our estimated model to carry out a historical decomposition of the variation in the gap between the natural rate and the actual real short rate, a measure of monetary policy stance. Our decomposition shows that news shocks account for a substantial fraction of cyclical movements in the gap between the natural and actual rates in the 1970s, in the 1990s and the early 2000s. Moreover, in all these periods monetary policy may have been excessively accommodative. This finding suggests that standard monetary policy rules of the type assumed in our model may not be sufficiently responsive to anticipated changes in fundamentals because such changes have only a moderate contemporaneous effect on the output gap and a countercyclical effect on inflation. Whereas this possibility has been pointed out by [Christiano et al. \(2010\)](#) in the context of a simulated stylized New-Keynesian model, our estimated model helps quantify this effect.

Our paper is related to the growing production-based asset pricing literature. See [Kaltenbrunner and Lochstoer \(2010\)](#), [Croce \(2014\)](#), [Kung and Schmid \(2015\)](#) to mention just a few contributions. Relative to these papers we propose an additional channel – changes in agents’ information due to the arrival of news – as an important source of co-movement between the macroeconomy and asset prices.

Our paper is also related to [Beaudry and Portier \(2006\)](#) and [Kurmman and Otrók \(2013\)](#), who show that stock prices and the slope of the term structure of interest rates are informative about news shocks. We make use of both variables in our estimation procedure. Differently from them, to investigate the importance of anticipated shocks for economic fluctuations we employ an estimated dynamic stochastic general equilibrium (DSGE) rather than a vector autoregression (VAR) analysis. Our analysis of the importance of news shocks through the lens of a DSGE 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 \(2017\)](#).

The information structure embedded in our model is inspired by [Schmitt-Grohe and](#)

Uribe (2012) and it delivers a new perspective on the long run-risk strand in consumption-based asset pricing literature dating back to Bansal and Yaron (2004) work. First, whereas the long-run risk literature has documented the importance of small changes in expectations about long-run fundamentals (see, e.g. Bansal et al., 2005), we instead consider large changes in expectations at business cycle horizon. Second, our analysis shows that there is heterogeneity in the timing of news and such heterogeneity is priced in the cross section using a variety of portfolios. Thus, our analysis complements that in Croce, Marchuk and Schlag (2017) who show that growth news shocks explain the premium paid by industries that lead aggregate economic fluctuations. Interestingly, whereas Croce et al. (2017) identify an anticipation horizon of about 27 quarters from the lead-lag relationships between GDP growth and industry-level cash-flow using reduced form regressions, our longer anticipation horizon is 8 quarters and it is obtained from a structural estimation of our news-driven model using aggregated macro and financial data. Future research should investigate how different estimation methods and dataset can convey information about the anticipation horizons of news shocks.

Finally, 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 cycles 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, as well as the lion's share of the nexus from confidence to future activity. More recently, Barsky, Basu and Lee (2015) exhaustively document that news shocks in total factor productivity exist, and are quantitatively important.

The rest of this paper is structured as follows. The next section introduces the model and describes the solution and estimation methodologies. Section 3 then discusses the estimation results and the role of news shocks in the model. Section 4 relates the model and news shocks to the natural rate of interest and the cross-section of stock and bond

returns. Section 5 concludes.

## 2 Macroeconomic Model

### 2.1 Model

*News.* Shocks to productivity  $A_t$  are the focus of our analysis. We specify productivity growth as autoregressive and subject to anticipated and unanticipated innovations:

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

where  $\epsilon_{0,t}$  are date  $t$  productivity surprises, while innovations  $\epsilon_{j,t-j}$  are anticipated  $j$  periods ahead: they affect date- $t$  productivity, but are period  $t - j$  information.<sup>5</sup> Our choice of modeling news shocks as anticipated *growth* shocks (i.e. technology asymptotes to a permanently higher level following a news shock, see Eq. (1)) is consistent with empirical evidence in e.g. Barsky et al. (2015).

Under independent and jointly normal shocks, Eq. (1) is observationally equivalent to a setting where agents receive noisy signals about the realization of future productivity, as shown in Chahrour and Jurado (2018). This equivalent information structure can be formally represented as

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

$$s_{1,t-1} = \epsilon_t + v_{1,t-1}, \quad (3)$$

$$s_{4,t-4} = \epsilon_t + v_{4,t-4}, \quad (4)$$

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<sup>5</sup>We borrow this specification from Schmitt-Grohe and Uribe (2012). We also consider additional shocks anticipated twelve and sixteen periods ahead. Empirically, we find that twelve-quarter news do not play a significant role. Sixteen quarter news considerably increase the number of state variables that track agents' expectations and are computationally challenging.

$$s_{8,t-8} = \varepsilon_t + \mathbf{v}_{8,t-8}, \quad (5)$$

where  $\mathbf{v}_{j,t-j}$  is the noise component of the signal  $s_{j,t-j}$  received  $j$  periods ahead of the realization of the productivity shock  $\varepsilon_t$ .<sup>6</sup>

The rest of the model is a version of the standard New-Keynesian framework.<sup>7</sup>

*Representative household.* The representative household owns the capital stock,  $K_t$ , and the claim to firms' profits,  $\Theta_t$ ; she chooses consumption  $C_t$ , labor  $L_t$ , and investment in capital  $I_t$  to maximize her lifetime utility  $U_t$  defined recursively<sup>8</sup>

$$U_t = \frac{C_t^{1-1/\psi}}{1 - \frac{1}{\psi}} - \eta_0 \frac{A_t^{1-1/\psi} L_t^{1+1/\eta}}{1 + \frac{1}{\eta}} + \beta \left[ E_t \left[ U_{t+1}^\gamma \right] \right]^{\frac{1}{\gamma}}, \quad (6)$$

subject to:

$$C_t + I_t = W_t L_t + R_{K,t} K_t + \Theta_t,$$

$$K_{t+1} = \left[ 1 - \delta + \zeta_1 \left( \frac{I_t}{K_t} \right)^\zeta + \zeta_2 \right] K_t, \quad (7)$$

$$W_t - W_{F,t}^{1-\rho_w} W_{t-1}^{\rho_w} = 0. \quad (8)$$

In the preferences specified by (6),  $\beta$  is the time discounting rate,  $\psi$  is the elasticity of inter-temporal substitution (EIS), and  $\eta$  is the Frisch elasticity. The relative risk aversion (RRA) is decreasing in  $\gamma$ . Capital accumulation in (7) is subject to adjustment costs that depend on  $\zeta$ . Real wages are subject to inertia captured by (8), where  $W_{F,t}$  is the wage determined by the Frisch labor supply relationship  $W_{F,t} = \eta_0 A_t^{1-1/\psi} L_t^{1/\eta} C_t^{1/\psi}$ .

*Firms.* There is a continuum of monopolistically competitive firms indexed by  $j \in$

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<sup>6</sup>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 \(2016\)](#).

<sup>7</sup>We opted for the most parsimonious model that matches the moments of interest. Additional features, such as variable capital utilization, do not improve on the model's performance.

<sup>8</sup>We present the case  $\frac{C_t^{1-1/\psi}}{1 - \frac{1}{\psi}} - \eta_0 \frac{A_t^{1-1/\psi} L_t^{1+1/\eta}}{1 + \frac{1}{\eta}} > 0$ . The opposite case is treated symmetrically. See [Swanson \(2012\)](#) for more details.

$[0, 1]$ . Every period each firm with probability  $1 - \theta$  has the opportunity to adjust its output price  $P_{o,t}(j)$  to maximize

$$E_t \left[ \sum_{s=0}^{\infty} \theta^s M_{\$,t,t+s} [P_{o,t}(j) Y_{t+s}(j) - P_{t+s} [W_{t+s} N_{t+s}(j) + R_{K,t+s} K_{t+s}(j)]] \right] \quad (9)$$

subject to

$$Y_{t+s}(j) = Z_{t+s} K_{t+s}(j)^\alpha (A_{t+s} N_{t+s}(j))^{1-\alpha}, \quad (10)$$

$$Y_{t+s}(j) = \left[ \frac{P_{o,t}(j)}{P_{t+s}} \right]^{-\varepsilon} Y_{t+s}, \quad (11)$$

where the aggregate price index  $P_t$  is given by

$$P_t = \left[ \int_0^1 P_t(j)^{1-\varepsilon} dj \right]^{\frac{1}{1-\varepsilon}} = [(1-\theta) P_{o,t}^{1-\varepsilon} + \theta P_{t-1}^{1-\varepsilon}]^{\frac{1}{1-\varepsilon}}. \quad (12)$$

The expression in (9) 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 capital  $K_t(j)$  and labor  $N_t(j)$  at real wage  $W_t$  and capital return rate  $R_{K,t}$ , respectively. The firms have identical production technology (10) that depends on permanent productivity shocks through  $A_t$  and transitory productivity shocks through  $Z_t$ , where

$$\ln Z_t = \rho_z \ln Z_{t-1} + \varepsilon_{z,t}. \quad (13)$$

The demand functions for firms' output is given by (11), where  $\varepsilon$  determines the mark-up charged by the firms.

*Monetary authority.* The monetary authority sets the one period (gross) nominal

interest rate  $R_{n,t}$  using a modified Taylor rule

$$R_{n,t} = R_{n,t-1}^{\rho_{rn}} \left[ R_n \left[ \frac{\Pi_t}{\Pi} \right]^{\phi_\pi} \left[ \frac{Y_t/A_t}{Y/A} \right]^{\phi_{y1}} \left[ \frac{Y_t/Y_{t-1}}{Y/Y_{-1}} \right]^{\phi_{y2}} \right]^{1-\rho_{rn}} e^{\varepsilon_{m,t}}, \quad (14)$$

where  $\Pi_t = P_t/P_{t-1}$  is the gross inflation rate,  $R_n$ ,  $\Pi$ ,  $Y/A$  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. (14) 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.

*Asset Prices.* 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.<sup>9</sup> 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  $\chi$ :

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

*Innovations.* 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.

*Equilibrium.* Together with the exogenously given Eqs. (1), (7), (8), (13)-(14), equilibrium is characterized by the set of conditions presented in Appendix A.1. The Appendix also shows that the specification of news in Eq. (1) can be rewritten in the state-space form, making the model amenable to standard solution methods.

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<sup>9</sup>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.

## 2.2 Solution, estimation, and filtering

*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.<sup>10</sup> 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.<sup>11</sup> 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.* In the estimation we employ the following macroeconomic and financial time series for the sample from 1970:Q1 to 2014:Q2: log output growth,  $\Delta y_t$ ; log consumption growth,  $\Delta c_t$ ; log investment growth,  $\Delta i_t$ ; one-quarter inflation,  $\Pi_t$ ; 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 co-

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<sup>10</sup>For example, a first-order approximation of the model is not able to generate a positive slope in the term structure of interest rates.

<sup>11</sup>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.

variances and the first auto-covariances in the data as moments. Hence, we let

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

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

$$\theta_{GMM} = \underset{\theta \in \Theta}{\operatorname{argmin}} \left( \frac{1}{T} \sum_{t=1}^T q_t - E[q_t(\theta)] \right)' W \left( \frac{1}{T} \sum_{t=1}^T q_t - E[q_t(\theta)] \right).$$

Here,  $W$  is a positive definite weighting matrix and  $E[q_t(\theta)]$  contains the model-implied moments. We use the conventional two-step implementation of GMM by letting  $W_T = \text{diag}(\hat{S}^{-1})$  in a preliminary first step to obtain  $\widehat{\theta^{\text{step 1}}}$  where  $\hat{S}$  denotes the long-run variance of  $\frac{1}{T} \sum_{t=1}^T q_t$  when re-centered around its sample mean. Our final estimates  $\widehat{\theta^{\text{step 2}}}$  are obtained using the optimal weighting matrix  $W_T = \text{diag}(\hat{S}_{\hat{\theta}^{\text{step 1}}}^{-1})$ , where  $\hat{S}_{\hat{\theta}^{\text{step 1}}}$  denotes the long-run variance of our moments re-centered around  $E[q_t(\widehat{\theta^{\text{step 1}}})]$ . 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.

*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, and the real stock market return. Importantly, our results are robust to changes in the number and identity of observables as well as length of the sample period as discussed in [Appendix A.5](#).

We employ 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. This methodology is very general and can be applied to a wide variety of models. In fact, we also consider a variant of our baseline model without news shocks, as discussed in section 4.1 below.

### 3 Estimation Results

This section presents parameter estimates, moments generated by the model, variance decomposition for model variables and their impulse responses to news shocks.

*Parameters.* The values of 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.

**[Insert Table 1 about here]**

Panel B reports our estimated parameters. The estimated magnitude of news shocks, a novel element in our model, is of particular interest. We find that the standard deviation of one-quarter 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%. 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.

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.

The literature provides several ways to interpret the estimated risk aversion parameter  $\gamma$ . [Swanson \(2012\)](#) shows that, after taking into account the labor margin, effective relative risk aversion is approximately equal to  $RRA \approx (\psi + \eta)^{-1} + (1 - \gamma) \left( \frac{1}{1 - 1/\psi} - \frac{1}{1 + 1/\eta} \right)^{-1}$ . Thus,  $\gamma = -85$  implies a relative risk aversion coefficient of approximately 45. [Andreassen and Jorgensen \(2018\)](#) argue that the effective risk aversion is even lower if one additionally takes into account the agents attitude towards the timing of risk. Importantly, the parameter  $\gamma$  does not have a significant effect on the dynamics of macroeconomic variables, even at higher orders (see also [Tallarini, 2000](#)). As such,  $\gamma$  is pinned down by the unconditional means of the price-to-dividend ratio and the slope of the term structure.

*Moments.* 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.

**[Insert Table 2 about here]**

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.<sup>12</sup> 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.

**[Insert Figure 1 about here]**

*The role of structural shocks.* Panel A of Table 3 decomposes the variability of endogenous model variables. The first row recovers the benchmark specification with all structural shocks being active with reported standard deviations identical to those in Table 2. The following rows document corresponding results when we consecutively set

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<sup>12</sup>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 e.g. [Croce, 2014](#)).

the realizations of all but one shock to zero. We find that news shocks to productivity generate substantial fluctuations in consumption. In fact, they account for around 26 ( $= 0.6^2/1.17^2$ ) percent of the observed variability in consumption. We will revisit this point in Section 4 when we relate news shocks to the stochastic discount factor. Further, news shocks are the key drivers of (business cycle) fluctuations in equity returns, the real rate, and the price-to-dividend ratio. They are responsible for 66 ( $= 11.59^2/14.24^2$ ), 40 ( $= 0.63^2/1^2$ ) and 15 ( $= 4.93^2/12.68^2$ ) percent of the variance of returns, the 1-quarter real rate, and the price-to-dividend ratio, respectively. We will discuss the link between news and asset prices in Section 4.1 and Section 4.2. Finally, news shocks explain a substantial fraction of inflation movements.

**[Insert Tables 3 about here]**

Panel B of the Table further studies shocks to productivity growth. We decompose the total variance induced by shocks to productivity growth along two dimensions: (1) into surprises and news and (2) into fundamental and noise components as in [Chahrour and Jurado \(2018\)](#). Both for macroeconomic variables as well as asset prices news are more important than surprises. In fact, news explain between 57 and 81 percent of the variation across model variables. An even clearer separation emerges for macroeconomic variables with respect to the fundamental and noise components. The noise components of the signals in equations (3) - (5) explain at most 15 percent of the variation. For asset prices, noise shocks are instead more important. In particular, noise 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.

*Impulse responses.* Next, we compare the impulse responses to a news shock implied by our model to those that can be identified in the data using a VAR. Different approaches proposed in the literature lead to different identifications of news shocks, highlighting the interest of our structural estimation. We follow [Barsky and Sims \(2011\)](#) and [Kurmann and Otrok \(2013\)](#), and run a vector autoregression (VAR) that combines a

measure of productivity – namely the utilization-adjusted total factor productivity (TFP) estimated by [Fernald \(2014\)](#) – with prominent macro aggregates and financial variables. As an alternative approach, we follow [Kurmann and Sims \(2017\)](#). More details about the data and the identification procedures are reported in Appendix [A.3](#).

Figures [2](#) and [3](#) show the impulse responses to a news shock. The red dashed lines refer to median responses and the red bands to corresponding 16 to 84 percent coverage intervals implied by the joint posterior distribution of VAR coefficients. The blue solid lines refer to model-implied responses computed as the weighted (by the volatility) average of the responses to one-, four- and eight quarters news shocks to allow the comparison with the VAR-implied responses that do not distinguish between news at different horizons. In our calculation of model responses we follow [Fernández-Villaverde et al. \(2015\)](#) and start the responses at the ergodic mean in absence of shocks, see appendix [A.4](#) for a detailed discussion.

**[Insert Figures [2](#) and [3](#) about here]**

As can be seen on Figures [2](#) and [3](#), the responses of the different variables to a news shock in the data and the model overlap closely. In response to a positive news shock, GDP and investment respond similarly to consumption with a gradual increase to a new permanent level. Further, both in the data and in the model, inflation and short-term interest rates drop markedly on impact of the news shock before slowly returning to their initial values. Lastly, news shocks lead to large and persistent changes in the stock market price-to-dividend ratio. In particular, in the data the price-to-dividend ratio jumps up to a level between 1 and 4% above its pre-shock value, and returns to it after about two years. The model replicates well these price dynamics.

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.

We conclude that the model fits the data well in terms of unconditional moments and dynamics.

## 4 Applications

In this section we present our main results on the implications of news shocks for interest rates, equity prices, and the macroeconomic risk in the economy.

For the return  $R_{i,t+1}$  on any asset  $i$ , including the risk-free rate of return  $R_{f,t}$ , we have

$$E_t [M_{t,t+1} R_{i,t+1}] = 1, \quad (15)$$

where the real stochastic discount factor  $M_{t,t+1}$  implied by household's preferences (6) is given by

$$M_{t,t+1} = \beta \left[ \frac{V_{t+1}}{E_t [V_{t+1}^\gamma]} \right]^{\gamma-1} \left[ \frac{C_{t+1}}{C_t} \right]^{-1/\psi}, \quad (16)$$

and  $V_t$  is the value function associated with household's maximization problem. Assuming, for expositional convenience, log-normality and denoting the logs of variables with lowercase letters, Eq. (15) implies

$$r_{f,t} + \frac{1}{2} \text{Var}_t [m_{t,t+1}] = -E_t [m_{t,t+1}], \quad (17)$$

$$E_t [r_{i,t+1} - r_{f,t}] + \frac{1}{2} \text{Var}_t [r_{i,t+1}] = -\text{Cov}_t [m_{t,t+1}, r_{i,t+1}]. \quad (18)$$

Given the observed path of the economy, allowing for latent information available to agents through anticipated shocks changes the decomposition of the (log) stochastic discount factor  $m_{t,t+1}$  into the expected component  $E_t [m_{t,t+1}]$  in Eq. (17) and the innovation  $m_{t,t+1} - E_t [m_{t,t+1}]$  that determines the conditional covariance in Eq. (18). Indeed,

household’s expectations of future macroeconomic outcomes, and thus of the stochastic discount factor, naturally depend on the realization of news shocks. Accounting for the part of the outcomes that has been anticipated based on prior information, by implication, changes the stochastic discount factor innovation, or risk. The estimated macroeconomic model allows us to infer the latent information available to agents. In this sense, it sheds new light on the factors driving the cross-section of expected returns and the natural rate of interest, which we consider in sequence.

## 4.1 Cross-section of stock returns

In this section we examine the performance of news-based macroeconomic risk factors in pricing the cross-section of asset returns.

To begin, we note that factors rooted in economic theory – namely, the static CAPM of Sharpe (1964) and Lintner (1965), the unconditional consumption CAPM (C–CAPM) of Breeden (1979), or a two-factor model combining CAPM and C–CAPM – have little explanatory power for the expected returns of 25 Fama-French size and book-to-market sorted portfolios, a standard set of test assets. This is illustrated in Panels A and B of Figure 4, which plots fitted expected against realized average returns for these portfolios, and Panel A of Table A.1 in the Appendix.<sup>13</sup>

**[Insert Figure 4 about here]**

This motivates us to test our model-implied factors. The estimated macroeconomic model allows us to test Eq. (18) by conditioning on investors’ information. Specifically,

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<sup>13</sup>The CAPM and C–CAPM factors are the return (in excess of the one-month T-bill rate from Ibbotson Associates) on the value-weighted stock market index and the growth rate in real per capita nondurable consumption (seasonally adjusted at annual rates) from the Bureau of Economic Analysis, respectively. In untabulated results, we find that, similar to the observed consumption growth rate, the consumption growth rate implied by the estimated model also has little explanatory power for the cross-section of expected returns. This is, perhaps, not surprising, given the model’s good match of observed macroeconomic dynamics.

we test

$$E[r_{i,t}^e] = \lambda_0 + \beta_{i,M} \lambda_M, \quad (19)$$

where  $\beta_{i,M}$  is the beta to the innovations in the recursive stochastic discount factor. To the first order, these innovations can be written as:

$$m_{t,t+1} - E_t[m_{t,t+1}] \approx m'_\varepsilon \varepsilon_{t+1},$$

where  $\varepsilon_t = [\varepsilon_{0,t} \varepsilon_{1,t} \varepsilon_{4,t} \varepsilon_{8,t} \varepsilon_{z,t} \varepsilon_{m,t}]'$  and  $m_\varepsilon < 0$  is a vector of coefficients determined by the model.<sup>14</sup>

Because the dynamics of the model, and thus the identification of news shocks, are effectively independent of  $\gamma$ , 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 (16). As a result, we have

$$E[r_{i,t}^e] = \lambda_0 + \beta_{i,Cnews} \lambda_{Cnews}, \quad (20)$$

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

$$c_{t+1} - E_t[c_{t+1}] \approx c'_\varepsilon \varepsilon_{t+1}.$$

The novelty of our factors lies in the shocks  $\varepsilon_t$  filtered from the model with news. Innovations in the Epstein-Zin stochastic discount factor and innovations in consumption growth can be intuitively understood as different combinations of these shocks: the stochastic discount factor implied by recursive utility puts significant weight on the longer-horizon news whereas consumption reacts more moderately to changes in ex-

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<sup>14</sup>See [Malkhozov \(2014\)](#) on how to compute risk-adjustments in log-linearized macroeconomic models. 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.

pected future productivity. Yet, even if the shock loadings are partly misspecified relative to the true stochastic discount factor, we show that a better identification of the elementary macroeconomic shocks in itself can improve on our ability to explain the cross-section of expected returns.<sup>15</sup>

Panels C and D of Figure 4 illustrate the respective performance of the model-implied consumption innovations and recursive stochastic discount factor innovations in explaining the average expected returns of the 25 Fama-French size and book-to-market sorted portfolios. In each panel, the respective factor has explanatory power across both sorting dimensions. Moreover, the observed relationship between factor beta and expected return is not driven by outlier portfolios.

Panel A of Table 4 examines the performance of the model-implied factors more formally. When accounting for the effect of news shocks on expected consumption, innovation in consumption attains an  $R^2$  of 44%. Analogous performance is obtained when relying on innovations in the stochastic discount factor. We also report the sampling variability in the  $R^2$  (see Kan et al., 2013): both  $R^2$ s are 1.5 standard deviation away from zero. Overall, this is a remarkable performance for a one-factor macro-based asset pricing model.

**[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 in Table 4 are jointly significantly different from zero. We reject the hypothesis at conventional

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<sup>15</sup>In this sense, our mechanism differs from the long-run risk models that rely on agents' preferences that put most weight on very long-horizon shocks.

significance levels. Similarly, we reject the hypothesis that all betas are equal to each other. See Appendix A.6 for detailed results.

The zero-beta rate and risk premium estimates further support the model-implied factors. For each factor, we report  $\hat{\lambda}$ s and associated  $t$ -ratios. In particular, we report the  $t$ -statistic of Fama and MacBeth (1973), followed by the GMM-corrected  $t$ -statistic which accounts for estimation error in the betas (see also Shanken, 1992; Jagannathan and Wang, 1998). The model-implied innovations in consumption have coefficients that are reliably positive at the 10% significance level, while the model-implied innovations in SDF are negatively priced, both in line with theoretical predictions.<sup>16</sup> In addition, the zero-beta rate for consumption innovations is not significantly larger than the risk-free rate. In fact, removing the constant, leads to only a mild reduction in cross-sectional  $R^2$  from 44% to 37%.

The model-implied factors in Panel A of Table 4 aggregate news shocks *and* the remaining shocks (surprise in permanent and transitory productivity, and monetary shocks). It is then natural to ask what is the individual contribution of news shocks with different anticipation horizons to cross-sectional variation in asset prices. To answer this question, Panel B of Table 4 considers a specification where we do not restrict the way news shocks enter the stochastic discount factor. In other words, we do not aggregate news shocks (together with the other shocks) into a single factor. Instead, we allow news at each horizon to represent a potentially independent source of risk with its own risk premium:

$$E[r_{i,t}^e] = \lambda_0 + \lambda_1 \beta_{i,1} + \lambda_4 \beta_{i,4} + \lambda_8 \beta_{i,8}, \quad (21)$$

where  $\beta_{i,j}$  is the beta of returns on asset  $i$  with the  $j$ -period anticipated news.<sup>17</sup> The

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<sup>16</sup>In contrast, as in many past studies, we find that the CAPM market factor is negatively priced, contrary to the theoretical prediction, see Panel A of Table A.1.

<sup>17</sup>The news-driven models in Eqs. (19) and (20) aggregate information in news shocks through either the SDF or consumption, and assign a unique premium to the risk carried by news shocks. The model specification in Eq. (21) assigns a risk premium to each news shock individually. As such, the latter specification is less restricted than the previous two and can shed light on the importance of considering

model 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 in Panel A. 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.

In addition, using the [Chahrour and Jurado \(2018\)](#) decomposition, we can assess the pricing of the noise component in news, which represents the anticipated changes in future productivity that eventually do not materialize.<sup>18</sup> Panel C of Table 4 shows that the cross-sectional  $R^2$  of a specification with only the noise component of news is lower compared with Panels A and B. At the same time, the risk premia for noise shocks are positive, significant for one- and eight-quarter horizons, and of the magnitude comparable to that of news at the same horizon. These results are in line with our interpretation of noise shocks. On the one hand, noise accounts for a smaller part of the fluctuations in macroeconomic variables and cannot on its own explain the cross-sectional variation in expected returns. On the other hand, agents cannot distinguish between the noise and the fundamental components of news, and price them in the same way.

Next, we further investigate the value added by news shocks.

First, we consider the ultimate consumption factor of [Parker and Julliard \(2005\)](#) who argue that the risk of a portfolio could be better measured by the covariance of its return with consumption growth over the quarter of the return and several subsequent quarters, namely  $\text{Cov}\left(r_{i,t+1}^e, \sum_{s=0}^S (c_{t+1+s} - c_{t+s})\right)$ . A similar measure is also employed by [Malloy, Moskowitz and Vissing-Jorgensen \(2009\)](#). In the context of our model, ultimate consumption can be interpreted as a noisy proxy for the realization of news shocks that determine fundamentals in several subsequent quarters. To compare the two competing measures of risk – ultimate consumption and consumption innovations

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longer anticipation horizons for news shocks.

<sup>18</sup>By construction, noise is orthogonal to the fundamental component of news.

implied by our news model – we run the following cross-sectional regressions

$$E[r_{i,t}^e] = \lambda_0 + \beta_{i,Cnews}\lambda_{Cnews} + \beta_{i,PJ}\lambda_{PJ}, \quad (22)$$

where we choose  $S = 11$  quarters as in [Parker and Julliard \(2005\)](#), and the betas are estimated from two separate univariate regressions.<sup>19</sup> Panel A of Table 5 reports the results for this two-factor model.<sup>20</sup> In the joint model that includes a constant,  $\lambda_{PJ}$  turns insignificant, whereas the price of our consumption innovation,  $\lambda_{Cnews}$ , remains significant. Moreover, the  $R^2$  from a regression that includes only consumption innovations is 0.43 (not reported): adding ultimate consumption increases the cross-sectional  $R^2$  by just 1 percentage point.<sup>21</sup> We conclude that our news-driven measure of risk captures macroeconomic risk more adequately than ultimate consumption.

Our model’s ability to capture consumption risk and explain the performance of consumption-based factors such as the one proposed by [Parker and Julliard \(2005\)](#) is further substantiated by Figure 5. The figure plots the covariance of the market returns  $r_{t+1}^e$  with future consumption growth  $c_{t+1+h} - c_t$  for  $h = 0, \dots, 24$  quarters along with 95% confidence bands constructed using Newey-West standard errors (dashed lines). In the data, the contemporaneous covariance ( $h = 0$ ) is non-zero. Its value increases up to 7 quarters. Beyond that time, the numbers decrease slightly with the horizon, but the confidence bands become larger. The figure shows that the covariance pattern in the data is well replicated by our news model.

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<sup>19</sup>As argued in [Kan et al. \(2013\)](#), using separate, simple regressions ensures that if the estimated price of risk  $\lambda_{Cnews}$  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.

<sup>20</sup>Table A.1 reports results for the one-factor model with ultimate consumption: we find a positive price of ultimate consumption risk that is marginally insignificant. The  $R^2$ s are comparable to those obtained in [Parker and Julliard \(2005\)](#) despite the different sample period.

<sup>21</sup>Note that the sample is different from that in Table 4 since we lose about 3 years of data to compute the forward looking ultimate consumption factor.

**[Insert Figure 5 about here]**

Second, we consider the asset pricing performance of a model without news shocks and show that news shocks are critical for our results. In untabulated results, we find that if we shut down news about productivity – keeping other estimated parameters the same – then the model pricing performance worsens dramatically. It follows that news shocks identified within our model are a key component of the aggregate macroeconomic risk. Based solely on this, however, we cannot rule out that a more parsimonious model without news could potentially achieve a similar pricing performance. Thus, to show the role of news, we re-estimate a version of our model that does not allow for news shocks and show that it cannot simultaneously fit the cross-section of expected asset returns and the consumption dynamics. The model without news performs worse than the model with news on several dimensions. Comparing Panel B of Table 5 with Panel A of Table 4, we observe that the factors implied by the model without news achieve a worse cross-sectional fit, with the  $R^2$  decreasing from 40% to 23% for the innovations in the recursive stochastic discount factor. For consumption innovations, the factor premium is no longer significant under the GMM standard errors. Moreover, the variability of the  $R^2$ s for both factors implied by the model without news is larger, making it hard to distinguish the one-factor model from a benchmark that includes only a constant risk premium across all assets. Most importantly, however, the pricing ability of the factors implied by the model without news comes at the cost of having a filtered consumption series that bears little resemblance to the data counterpart. In fact, the correlation between data and the filtered consumption series for the model without news is 26%, a much lower value compared to the 59% attained by the baseline model. In other words, in the model without news, the measurement error accounts both for low variability of consumption innovations and large dispersion in asset prices.

**[Insert Table 5 about here]**

Finally, Table 6 shows that our results hold in alternative cross-sections of assets.

Panel A of Table 6 shows results for the model-implied SDF when, similar to Kan, Robotti and Shanken (2013), 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). 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 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%).

Panel B in Table 6 reports further results for the 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 4.9% (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 50 basis points. Importantly, however, Koijen, Lustig and Van Nieuwerburgh (2017) rely on a model with three priced risk factors that are tradeable (e.g. a combination of forward rates in the spirit of Cochrane and Piazzesi, 2005). This stands in stark contrast to our single macroeconomic factor model. In untabulated results we show that our model largely eliminates most of the value spread, and it also matches the market equity risk premium and the bond risk premium on long-term maturity bonds (5- and 10-years).

The estimates of horizon-specific risk premia reinforce this latter point. For the cross-section of stock and bond returns in Panel B, the model with unrestricted news shocks delivers excellent performance - at par of the news-driven SDF. However, these

test assets comprise just five value-growth equity portfolios, and display a reduced cross-sectional dispersion in equity returns compared to the 25 Fama-French portfolios. This fact does not allow for a strong identification of the risk premium carried by news shocks, except for the one associated with the very short one-quarter anticipation horizon. On the other hand, when we enlarge the cross-section of equity including the 25 Fama-French portfolios (with and without industries portfolios, see Panel B of Table 4 and Panel A of Table 6, respectively) we are able to recover a strong premium associated with long-term eight-quarters news besides that of the one-quarter news.

Panel C presents results for the duration-sorted portfolios constructed by [Weber \(2018\)](#). The author creates a measure of cash flow duration at the firm level using balance sheet data, sorts stocks into ten portfolios with increasing 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 cannot explain the novel cross section. Particularly important for our analysis is the fact that the ultimate consumption risk of [Parker and Julliard \(2005\)](#) and [Malloy, Moskowitz and Vissing-Jorgensen \(2009\)](#) cannot explain the duration-sorted cross section either. In contrast, our model continues to perform well also when it faces this challenging cross section. In particular, the premium of our news-driven SDF remains statistically significant. However, comparing the news-driven SDF with an unrestricted model that uses news at various anticipation horizons, we observe a significant increase in cross-sectional  $R^2$  – from 53% to 92% – with a simultaneous reduction of its variability. This evidence points to the fact that the restriction imposed by our model may be too stringent. At the same time we find comforting that our results for duration-sorted portfolios are similar to those obtained for value portfolios (see Panel B of Table 4 and Panel A of Table 6) since growth stocks are often thought to have high cash flow duration but low returns, and the opposite for value. Specifically both for value-growth and duration-sorted assets, we find evidence that the one-quarter and eight quarter news

carry a statistically significant, positive premium.

[Insert Table 6 about here]

## 4.2 Natural rate of interest

We define the natural rate of interest as the real short rate in the counterfactual economy without nominal rigidities.<sup>22</sup> This rate is not influenced by monetary policy decisions and captures the real forces, such as news about future productivity, driving the movements in interest rates.

As such, the natural rate provides an important monetary policy benchmark (see [Curdia, Ferrero, Ng and Tambalotti, 2015](#)): a monetary policy strategy that aims to bring the actual real rate in line with the natural rate is optimal in a baseline New-Keynesian model ([Woodford, 2003](#)) and is likely to remain close to optimal in models with additional trade-offs (see [Justiniano, Primiceri and Tambalotti, 2013](#)). In practice, monetary policy rules typically assume a constant natural rate of interest, see e.g. [Carlstrom and Fuerst \(2016\)](#). There are at least two possible reasons for this. First, the desire for the rule to be a function of easily observed variables only. Second, the implicit assumption that the natural rate of interest varies little over the business cycle frequency or that only its permanent changes are to be taken into account.<sup>23</sup>

The estimated model implies that the natural rate fluctuates considerably, and that news shocks play a key role in accounting for these movements: the annualized standard deviation of the log natural rate  $r_t^*$  is 63 basis points when all shocks are active, and 41 basis points when only news shocks are active while other shocks are set to zero. To

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<sup>22</sup> See [Wicksell \(1936\)](#), and more recently [Woodford \(2003, Ch. 4.1–4.2\)](#), [Barsky, Justiniano and Melosi \(2014\)](#), and [Del Negro, Giannone, Giannoni and Tambalotti \(2017\)](#).

<sup>23</sup> This assumption is sometimes made formal through the distinction drawn between the natural rate of interest, also referred to as Wicksellian natural rate, and the long-run equilibrium interest rate. See [Kiley \(2015\)](#) for a discussion.

understand the contribution of news, note that, to the first order, Eqs. (16) and (17) imply

$$r_t^* \approx \frac{1}{\psi} E_t (c_{t+1}^* - c_t^*) + \text{constant},$$

where  $r_t^*$  is the log of the natural rate of interest and  $c_t^*$  is the log of consumption in the counterfactual economy without nominal rigidities. News about future productivity translate into fluctuations in expected future consumption growth and, as a result, into fluctuations in the natural rate of interest.

To gauge the economic importance of news-driven fluctuations in the natural rate, we consider the difference between  $r_t^*$  and the actual real rate  $r_t$  implied by the model. The annualized standard deviation of  $r_t^* - r_t$  is 38 basis points when all shocks are active, and 27 basis points when only news shocks are active. Figure 6 plots the history of  $r_t^* - r_t$  implied by the model. As shown in Panel A of the figure, news explain an important part of the  $r_t^* - r_t$  difference, in particular in the later part of the sample starting from mid 1990s.

**[Insert Figure 6 about here]**

Several periods are noteworthy. Between 2000 and 2007, the annualized actual rate was approximately 50 basis points lower than the natural rate. This finding is in line with the argument that monetary policy may have been excessively accommodative in the run up to the Global Financial Crisis.<sup>24</sup> We also find that the actual real rates were lower than the natural rate - hence policy was on average stimulative - during the early 1970s, consistent with the fact that inflation rose steadily during that period; and between 1990 and 1994, when the Federal Reserve reacted aggressively to the 1991 recession by bringing real rates close to zero. In contrast, the actual real rate was higher than the natural rate between 2011 and 2015, consistent with the fact that in practice

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<sup>24</sup>See, for instance, [Taylor \(2009\)](#).

zero lower bound limited monetary authority's ability to stimulate the economy. Importantly, in all these periods most of the difference between natural and real rates is explained by the contribution of news shocks.<sup>25</sup>

To see why news shocks lead to deviations between  $r_t^*$  and  $r_t$ , compare their responses to positive news about future productivity. Upon a news shock, the natural rate increases, in line with the increase in expected future consumption growth. Unlike the natural rate, the actual rate  $r_t$  is influenced by monetary policy. The policy rule (14) assumes that the natural rate is constant at its steady state, but allows for the monetary authority's response to output growth, a measure of output gap, and inflation. Thus, by construction, the rule does not take into account the response of the natural rate to news. Moreover, since news do not have an immediate effect on current productivity, the response of output is muted, while inflation falls, as can be seen in Figure 2. As a result, the nominal short rate falls, pushing the real rate away from the natural rate.

Our results suggest that, in order to keep the actual real rate in line with the natural rate (provided it is part of its objective), the monetary authority should take into account the time-variation in the natural rate, and in particular the component of this time-variation driven by news. While these variables are not readily observable, asset prices can be used as a proxy for their fluctuations. Indeed, as can be seen from Figure 2, because of their forward-looking nature, both the term spread and the price-to-dividend ratio react strongly to news. Interestingly, the rationale for considering financial variables for monetary policy decisions does not rely on financial frictions, unlike in the recent policy discussion.<sup>26</sup> Instead, it stems from the informativeness of asset prices about news shocks that have a large effect on future economic conditions but only a

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<sup>25</sup>These periods align well with the evidence in Barsky et al. (2015) who document that news shocks play an important role in explaining inflation fluctuations during the 1970s and early 1980s, as well as in the 1990s and the first decade of the twenty-first century. Interestingly, our analysis derives from series filtered from a structural model, whereas the evidence in Barsky et al. (2015) is based on a reduced form, VAR historical decomposition.

<sup>26</sup>See, for instance, Borio (2014) and Stein (2014).

limited effect contemporaneously. In contrast, other forward-looking variables may not capture news shocks well. To illustrate this, we consider the monetary policy rule proposed in [Clarida et al. \(2000\)](#) in which the monetary authority responds to expected future inflation rather than to realized inflation. More formally, instead of Eq. (14), we assume

$$R_{n,t} = R_{n,t-1}^{\rho_{rn}} \left[ R_n \left[ \frac{E_t[\Pi_{t+1}]}{\Pi} \right]^{\phi_{\pi}} \left[ \frac{Y_t/A_t}{Y/A} \right]^{\phi_{y1}} \left[ \frac{Y_t/Y_{t-1}}{Y/Y_{-1}} \right]^{\phi_{y2}} \right]^{1-\rho_{rn}} e^{\mu_{n,t}}, \quad (23)$$

keeping all the parameters at the same values as for Eq. (14). Panel B of Figure 6 shows that the path of  $r_t^* - r_t$  is very similar under the baseline and the alternative monetary policy rules. In fact, in response to news (we choose one-quarter news to match the expected inflation horizon), inflation under the alternative rule falls by more than under the baseline rule, as shown on Figure A.2 in the Appendix.

We conclude this section by pointing out that our analysis does not speak to the possible secular trends in the natural rate of interest, a related topic recently explored in the literature.<sup>27</sup> Instead, our focus is on the cyclical variation in the natural rate that we find to be economically significant. At the same time, measuring the cyclical variation explicitly could in itself help with the “pile-up” problem associated with estimating a permanent component of the interest rate subject to substantial short-to-medium run variation.<sup>28</sup>

## 5 Conclusion

In this paper we explore the qualitative and quantitative implications of the expectation-driven view of business cycle fluctuations for interest rates and asset risk premia.

<sup>27</sup>See, for instance, [Summers \(2014\)](#) and [Eggertsson, Mehrotra and Robbins \(2018\)](#).

<sup>28</sup>See [Laubach and Williams \(2003\)](#), [Kiley \(2015\)](#), and [Holston et al. \(2017\)](#) for a simple, trend/cycle estimation of the secular trend in the natural rate, i.e. the equilibrium real interest rate, and the issues associated with this approach.

We show that accounting for agents' expectations results in a better measurement of macroeconomic risk. A better identification of macroeconomic risk, in turn, can improve our ability to explain the cross-section of expected returns, helping resolve an important failure of 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. The risk factors implied by our model could be applied to other asset pricing puzzles, a task that we leave to future research.

Moreover, we show that expectation shocks contribute to the variation in the natural rate of interest, an important monetary policy benchmark. Monetary policy rules can take this variation into account through forward-looking financial variables, such as the term spread or the price-to-dividend ratio. This rationale for including financial variables in the monetary policy rule does not not rely on financial frictions, unlike in recent policy discussion.

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## 6 Tables

TABLE 1: **Model Parameters.** This table reports the calibrated (Panel A) and estimated (Panel B) model parameters. Note that the parameter values of  $\mu_a$ ,  $\sigma_a$ ,  $\sigma_{1Q}$ ,  $\sigma_{4Q}$ ,  $\sigma_{8Q}$ ,  $\sigma_z$ , and  $\sigma_m$  are expressed in percent.

| Panel A: Calibrated Parameters |                          |                              |                         |                                  |                          |
|--------------------------------|--------------------------|------------------------------|-------------------------|----------------------------------|--------------------------|
| <u>Firm:</u>                   |                          |                              | <u>Monetary Policy:</u> |                                  |                          |
| $\delta$                       | capital depreciation     | 0.030                        | $\Pi$                   | steady-state inflation           | 1.008                    |
| $\alpha$                       | capital share            | 0.360                        | $\rho_r$                | AR(1) short rate                 | 0.70                     |
| $\theta$                       | price rigidity           | 0.760                        | $\phi_\pi$              | TR coefficient inflation gap     | 1.500                    |
| $\rho_w$                       | wage rigidity            | 0.900                        | $\phi_{y1}$             | TR coefficient output growth     | 0.700                    |
| $\chi$                         | leverage                 | 3.000                        | $\phi_{y2}$             | TR coefficient output gap        | 0.080                    |
| Panel B: Estimated Parameters  |                          |                              |                         |                                  |                          |
| <u>Preferences:</u>            |                          |                              | <u>Shocks:</u>          |                                  |                          |
| $\beta$                        | time discount            | 0.995<br>[0.994,0.996]       | $\mu_a$                 | steady-state productivity growth | 0.401<br>[0.378,0.422]   |
| $\gamma$                       | curvature                | -85.000<br>[-97.303,-73.301] | $\rho_a$                | AR(1) productivity               | 0.360<br>[0.312,0.395]   |
| $\psi$                         | IES                      | 1.650<br>[1.556,1.774]       | $\sigma_a$              | volatility productivity          | 0.505<br>[0.461,0.548]   |
| $\eta$                         | Frisch elasticity        | 1.800<br>[1.660,1.948]       | $\sigma_{1Q}$           | volatility 1Q news               | 0.498<br>[0.429,0.562]   |
|                                |                          |                              | $\sigma_{4Q}$           | volatility 4Q news               | 0.501<br>[0.471,0.531]   |
|                                |                          |                              | $\sigma_{8Q}$           | volatility 8Q news               | 0.199<br>[0.121,0.290]   |
| $\varepsilon$                  | mark-ups                 | 13.500<br>[11.633,15.189]    | $\rho_z$                | AR(1) technology                 | 0.975<br>[0.9614,0.9866] |
| $\zeta$                        | capital adjustment costs | 0.940<br>[0.931,0.948]       | $\sigma_z$              | volatility technology            | 0.722<br>[0.663,0.781]   |
|                                |                          |                              | $\sigma_m$              | volatility monetary policy       | 0.210<br>[0.201,0.223]   |

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 2014.Q2. 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, the price-to-dividend (PD) ratio is adjusted to account for business cycles. 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<br>[2.77,3.28] | 0.85<br>[0.84,0.86]    | 1.00                   | 1.54                   | 0.87  | 1.00      |       |           |
| Consumption              | 1.17<br>[1.10,1.29] | 0.91<br>[0.89,0.92]    | 0.82<br>[0.75,0.86]    | 1.27                   | 0.89  | 0.88      |       |           |
| Investment               | 7.63<br>[7.06,8.83] | 0.78<br>[0.77,0.80]    | 0.98<br>[0.96,0.98]    | 7.07                   | 0.85  | 0.92      |       |           |
| Inflation                | 1.20<br>[0.81,1.52] | 0.87<br>[0.84,0.92]    | 0.06<br>[0.05,0.07]    | 0.61                   | 0.89  | 0.11      |       |           |
| Non-Targeted Moments:    |                     |                        |                        |                        |       |           |       |           |
| Wages                    | 0.63<br>[0.59,0.70] | 0.92<br>[0.91,0.93]    | 0.20<br>[0.18,0.22]    | 0.93                   | 0.68  | 0.09      |       |           |
| 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<br>[4.41,7.63] | 3.75<br>[2.75,6.07]    | 0.92<br>[0.88,0.95]    | 0.06<br>[0.03,0.09]    | 5.62  | 3.88      | 0.94  | 0.22      |
| Slope                    | 1.23<br>[0.84,1.98] | 1.82<br>[1.65,2.12]    | 0.84<br>[0.81,0.85]    | -0.29<br>[-0.34,-0.25] | 1.23  | 2.09      | 0.77  | -0.47     |
| PD Ratio                 | 0.02<br>[0.01,0.03] | 12.68<br>[10.26,18.23] | 0.97<br>[0.96,0.99]    | -0.19<br>[-0.23,-0.13] | 0.06  | 24.83     | 0.93  | 0.10      |
| Non-Targeted Moments:    |                     |                        |                        |                        |       |           |       |           |
| Nominal 5Y               | 6.62<br>[5.44,9.00] | 2.65<br>[1.65,4.89]    | 0.96<br>[0.94,0.98]    | -0.07<br>[-0.10,-0.03] | 6.34  | 3.06      | 0.97  | 0.00      |
| Nominal 10Y              | 6.84<br>[5.62,9.53] | 2.11<br>[1.21,4.23]    | 0.98<br>[0.95,0.98]    | -0.09<br>[-0.12,-0.05] | 6.84  | 2.71      | 0.97  | -0.05     |
| Real 2Y                  | 1.71<br>[1.41,1.96] | 0.70<br>[0.66,0.77]    | 0.89<br>[0.89,0.90]    | 0.04<br>[0.02,0.06]    | 1.87  | 1.80      | 0.89  | 0.10      |
| Real Equity Returns      | 8.23<br>[7.25,9.40] | 14.24<br>[13.46,15.21] | -0.04<br>[-0.04,-0.03] | -0.23<br>[-0.21,-0.25] | 5.66  | 36.29     | 0.07  | -0.08     |

TABLE 3: **The Role of Structural Shocks.** Panel A details the role of the different structural shocks in the baseline model. *A* and *Z* stand for permanent and transitory productivity, respectively. *News* and *Monetary* refer to three news shocks and the monetary policy shock. Panel A reports standard deviations of macro variables and asset prices obtained from simulated model data when all or only a subset of structural shocks are enabled. Panel B reports a variance decomposition of permanent productivity shocks into surprises and news and fundamental and noise, respectively. Panel B reports relative percentages of the total variance induced by the corresponding shocks. 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.

| Panel A: The Role of Structural Shocks        |            |             |            |         |           |                |
|-----------------------------------------------|------------|-------------|------------|---------|-----------|----------------|
| Macro Variables                               |            |             |            |         |           |                |
|                                               | Output     | Consumption | Investment | Wages   | Inflation |                |
| All Shocks                                    | 2.94       | 1.17        | 7.63       | 0.63    | 4.79      |                |
| Only A                                        | 1.11       | 0.52        | 2.59       | 0.26    | 1.07      |                |
| Only Z                                        | 2.02       | 0.79        | 5.38       | 0.40    | 4.47      |                |
| Only News                                     | 1.38       | 0.60        | 3.39       | 0.34    | 1.45      |                |
| Only Monetary                                 | 1.05       | 0.32        | 2.79       | 0.15    | 0.74      |                |
| Asset Prices                                  |            |             |            |         |           |                |
|                                               | Nominal 1Q | Nominal 10Y | Slope      | Real 1Q | PD-Ratio  | Equity Returns |
| All Shocks                                    | 3.75       | 2.12        | 1.82       | 1.00    | 12.68     | 14.24          |
| Only A                                        | 0.45       | 0.10        | 0.38       | 0.41    | 2.41      | 7.64           |
| Only Z                                        | 3.64       | 2.13        | 1.61       | 0.69    | 11.59     | 2.19           |
| Only News                                     | 0.74       | 0.16        | 0.62       | 0.63    | 4.93      | 11.59          |
| Only Monetary                                 | 0.36       | 0.02        | 0.35       | 0.16    | 1.21      | 0.69           |
| Panel B: Decomposition of Productivity Shocks |            |             |            |         |           |                |
| Macro Variables                               |            |             |            |         |           |                |
|                                               | Output     | Consumption | Investment | 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     |                |
| Noise                                         | 3.46       | 6.30        | 7.43       | 1.20    | 14.77     |                |
| Asset Prices                                  |            |             |            |         |           |                |
|                                               | Nominal 1Q | Nominal 10Y | Slope      | Real 1Q | PD-Ratio  | Equity 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          |
| Noise                                         | 29.30      | 19.85       | 29.07      | 6.75    | 22.41     | 68.95          |

TABLE 4: **Baseline Cross-Sectional Results.** We estimate cross-sectional regressions with and without a constant. In particular, the table reports results from running the cross-sectional regression

$$\overline{R}_i^e = (\gamma) + \beta_i \lambda + \alpha_i,$$

where  $\overline{R}_i^e$  is the mean excess return of portfolio  $i$  and  $\beta_i$  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  $\hat{\lambda}$  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  $\hat{\alpha}$ . The last column reports the  $R^2$  of the cross-sectional regression, and, for the model with the constant, 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.

| Panel A: Model-based factors                 |                                    |                                     |                                    |       |                  |                  |                |
|----------------------------------------------|------------------------------------|-------------------------------------|------------------------------------|-------|------------------|------------------|----------------|
| Constant                                     | $\lambda_C$                        | $\lambda_{SDF}$                     | RMSE                               | MAPE  | Joint $p$ -value | $R^2$            |                |
|                                              | <b>0.004</b><br>(0.001)<br>{0.002} |                                     | 2.067                              | 1.501 | 0.000            | 0.37             |                |
| 0.007<br>(0.008)<br>{0.013}                  | <b>0.003</b><br>(0.001)<br>{0.001} |                                     | 1.949                              | 1.347 | 0.000            | 0.44<br>(0.29)   |                |
|                                              |                                    | -1.275<br>(0.375)<br>{1.167}        | 3.822                              | 2.992 | 0.000            | -1.16            |                |
| 0.016<br>(0.008)<br>{0.011}                  |                                    | <b>-0.471</b><br>(0.159)<br>{0.244} | 2.019                              | 1.493 | 0.000            | 0.40<br>(0.27)   |                |
| Panel B: News shocks as independent factors  |                                    |                                     |                                    |       |                  |                  |                |
| Constant                                     | $\lambda_{1Q}$                     | $\lambda_{4Q}$                      | $\lambda_{8Q}$                     | RMSE  | MAPE             | Joint $p$ -value | $R^2$          |
|                                              | 0.642<br>(0.213)<br>{0.545}        | 0.479<br>(0.231)<br>{0.547}         | 0.419<br>(0.166)<br>{0.453}        | 2.857 | 2.329            | 0.000            | -0.21          |
| 0.014<br>(0.007)<br>{0.012}                  | <b>0.299</b><br>(0.113)<br>{0.116} | 0.187<br>(0.135)<br>{0.159}         | <b>0.162</b><br>(0.063)<br>{0.074} | 1.804 | 1.379            | 0.000            | 0.52<br>(0.22) |
| Panel C: Noise shocks as independent factors |                                    |                                     |                                    |       |                  |                  |                |
| Constant                                     | $\lambda_{1Q}$                     | $\lambda_{4Q}$                      | $\lambda_{8Q}$                     | RMSE  | MAPE             | Joint $p$ -value | $R^2$          |
|                                              | 0.370<br>(0.150)<br>{0.268}        | 0.563<br>(0.193)<br>{0.329}         | 0.470<br>(0.114)<br>{0.233}        | 2.555 | 2.129            | 0.000            | 0.00           |
| 0.028<br>(0.008)<br>{0.012}                  | <b>0.340</b><br>(0.145)<br>{0.174} | 0.285<br>(0.174)<br>{0.173}         | <b>0.211</b><br>(0.075)<br>{0.078} | 2.217 | 1.833            | 0.000            | 0.25<br>(0.29) |

TABLE 5: **Additional Cross-Sectional Tests.** We estimate cross-sectional regressions with and without a constant. In particular, the table reports results from running the cross-sectional regression

$$\overline{R}_i^e = (\gamma) + \beta_i \lambda + \alpha_i,$$

where  $\overline{R}_i^e$  is the mean excess return of portfolio  $i$  and  $\beta_i$  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  $\hat{\lambda}$  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  $\hat{\alpha}$ . The last column reports the  $R^2$  of the cross-sectional regression, and, for the model with the constant, 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.

| Panel A: Comparison with Parker and Julliard (2005) |                                    |                                     |       |       |                  |                |
|-----------------------------------------------------|------------------------------------|-------------------------------------|-------|-------|------------------|----------------|
| Constant                                            | $\lambda_C$                        | $\lambda_{PJ}$                      | RMSE  | MAPE  | Joint $p$ -value | $R^2$          |
|                                                     | 0.003<br>(0.001)<br>{0.002}        | 0.017<br>(0.011)<br>{0.017}         | 2.137 | 1.616 | 0.000            | 0.37           |
| 0.007<br>(0.009)<br>{0.011}                         | <b>0.002</b><br>(0.001)<br>{0.001} | 0.010<br>(0.012)<br>{0.016}         | 2.009 | 1.496 | 0.000            | 0.44<br>(0.23) |
| Panel B: Model without news                         |                                    |                                     |       |       |                  |                |
| Constant                                            | $\lambda_C$                        | $\lambda_{SDF}$                     | RMSE  | MAPE  | Joint $p$ -value | $R^2$          |
|                                                     | 0.005<br>(0.002)<br>{0.004}        |                                     | 2.247 | 1.644 | 0.000            | 0.25           |
| 0.008<br>(0.007)<br>{0.013}                         | 0.003<br>(0.001)<br>{0.002}        |                                     | 2.099 | 1.498 | 0.000            | 0.35<br>(0.34) |
|                                                     |                                    | -0.849<br>(0.243)<br>{0.922}        | 5.032 | 3.814 | 0.000            | -2.75          |
| <b>0.019</b><br>(0.008)<br>{0.010}                  |                                    | <b>-0.220</b><br>(0.090)<br>{0.112} | 2.277 | 1.809 | 0.000            | 0.23<br>(0.33) |

TABLE 6: **Alternative Cross-Sections.** We estimate cross-sectional regressions with and without a constant. In particular, the table reports results from running the cross-sectional regression

$$\overline{R}_i^e = (\gamma) + \beta_i \lambda + \alpha_i,$$

where  $\overline{R}_i^e$  is the mean excess return of portfolio  $i$  and  $\beta_i$  is the vector of factor betas of portfolio  $i$  estimated in the first-pass regression. In Panel A the models are estimated using quarterly excess returns on the 25 Fama-French size and book-to-market ranked portfolios and five industry 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. Finally, in Panel C the models are estimated using quarterly excess returns on the ten portfolios sorted on cash flow duration (see [Weber \(2018\)](#)). The table reports the estimates of the factor risk premia  $\hat{\lambda}$  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  $p$ -values). To compute the test statistic we use the OLS covariance matrix of  $\hat{\alpha}$ . The last column reports the  $R^2$  of the cross-sectional regression, and, for the model with the constant, 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.

| Panel A: 25FF and Industry Portfolio |                                     |                                    |                             |                                    |       |       |                  |                |
|--------------------------------------|-------------------------------------|------------------------------------|-----------------------------|------------------------------------|-------|-------|------------------|----------------|
| Constant                             | $\lambda_{SDF}$                     | $\lambda_{1Q}$                     | $\lambda_{4Q}$              | $\lambda_{8Q}$                     | RMSE  | MAPE  | Joint $p$ -value | $R^2$          |
| 0.015<br>(0.008)<br>{0.011}          | <b>-0.458</b><br>(0.166)<br>{0.256} |                                    |                             |                                    | 1.977 | 1.514 | 0.000            | 0.38<br>(0.29) |
| 0.014<br>(0.007)<br>{0.011}          |                                     | <b>0.286</b><br>(0.113)<br>{0.117} | 0.188<br>(0.130)<br>{0.153} | <b>0.156</b><br>(0.067)<br>{0.076} | 1.815 | 1.431 | 0.000            | 0.46<br>(0.22) |
| Panel B: Bond and Stock Portfolios   |                                     |                                    |                             |                                    |       |       |                  |                |
| Constant                             | $\lambda_{SDF}$                     | $\lambda_{1Q}$                     | $\lambda_{4Q}$              | $\lambda_{8Q}$                     | RMSE  | MAPE  | Joint $p$ -value | $R^2$          |
| <b>0.008</b><br>(0.002)<br>{0.003}   | <b>-0.756</b><br>(0.310)<br>{0.449} |                                    |                             |                                    | 1.139 | 1.029 | 0.000            | 0.89<br>(0.12) |
| 0.008<br>(0.003)<br>{0.007}          |                                     | <b>0.851</b><br>(0.392)<br>{0.457} | 0.854<br>(0.463)<br>{1.196} | 0.163<br>(0.106)<br>{0.271}        | 1.117 | 0.910 | 0.005            | 0.89<br>(0.12) |
| Panel C: Duration Portfolios         |                                     |                                    |                             |                                    |       |       |                  |                |
| Constant                             | $\lambda_{SDF}$                     | $\lambda_{1Q}$                     | $\lambda_{4Q}$              | $\lambda_{8Q}$                     | RMSE  | MAPE  | Joint $p$ -value | $R^2$          |
| <b>0.048</b><br>(0.012)<br>{0.019}   | <b>-0.689</b><br>(0.160)<br>{0.288} |                                    |                             |                                    | 2.618 | 1.576 | 0.000            | 0.53<br>(0.47) |
| <b>0.054</b><br>(0.010)<br>{0.019}   |                                     | <b>0.543</b><br>(0.125)<br>{0.219} | 0.298<br>(0.121)<br>{0.211} | <b>0.213</b><br>(0.058)<br>{0.102} | 1.079 | 0.953 | 0.000            | 0.92<br>(0.07) |

## 7 Figures

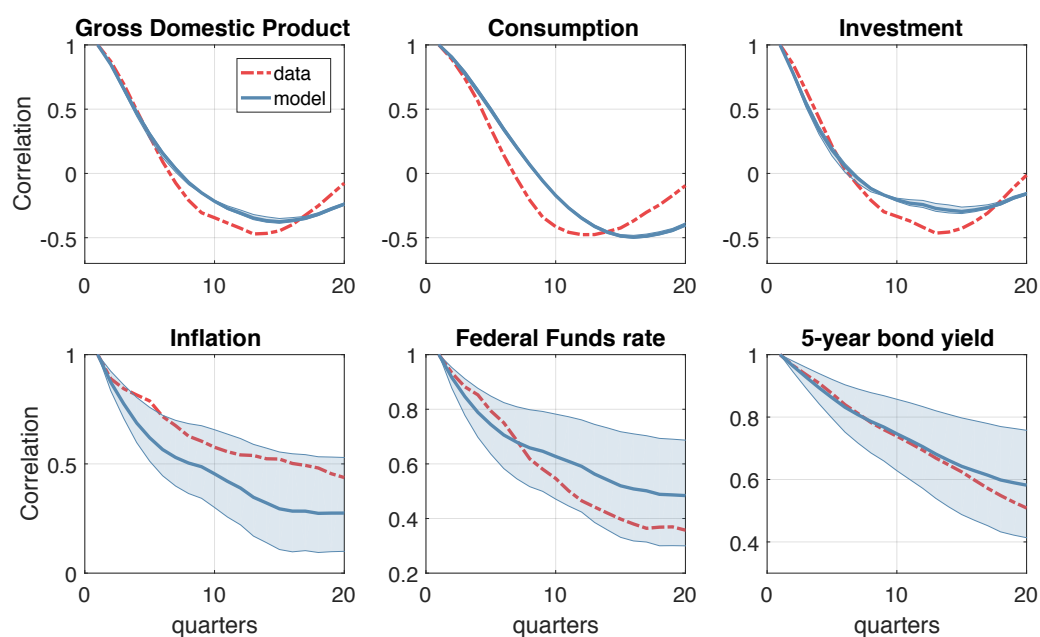
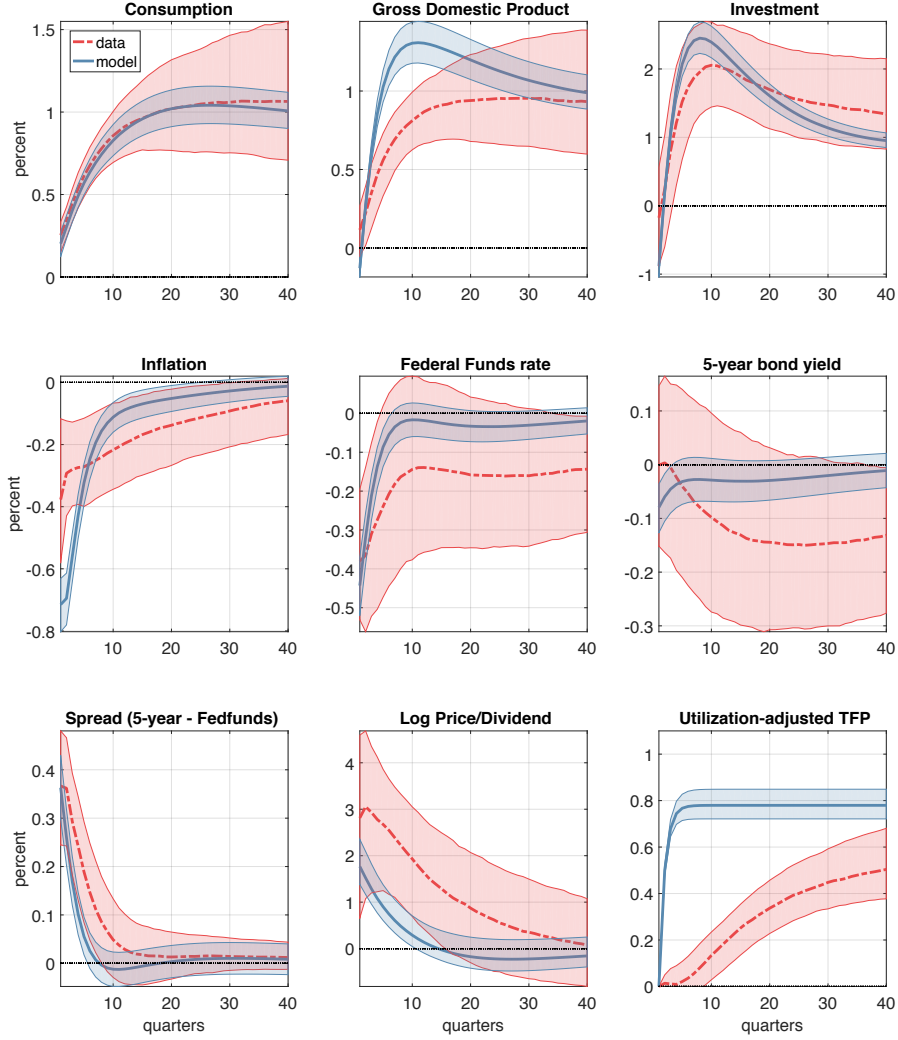
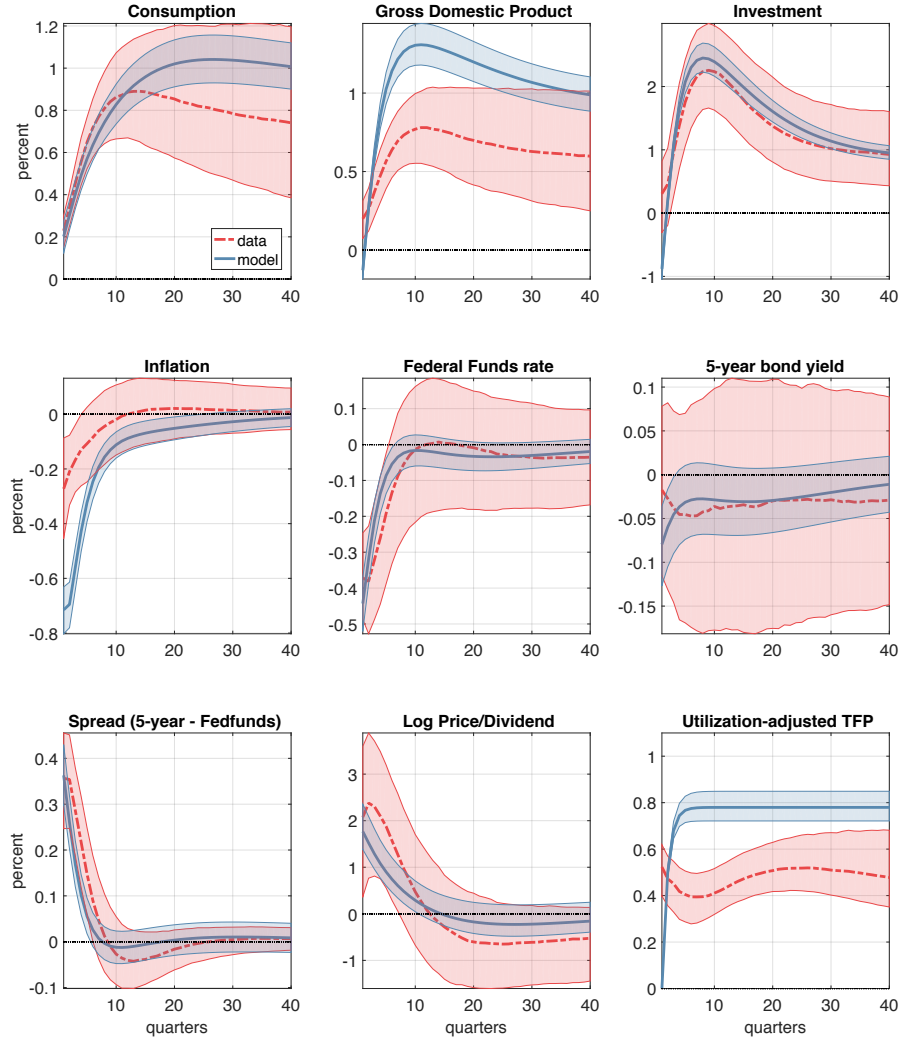


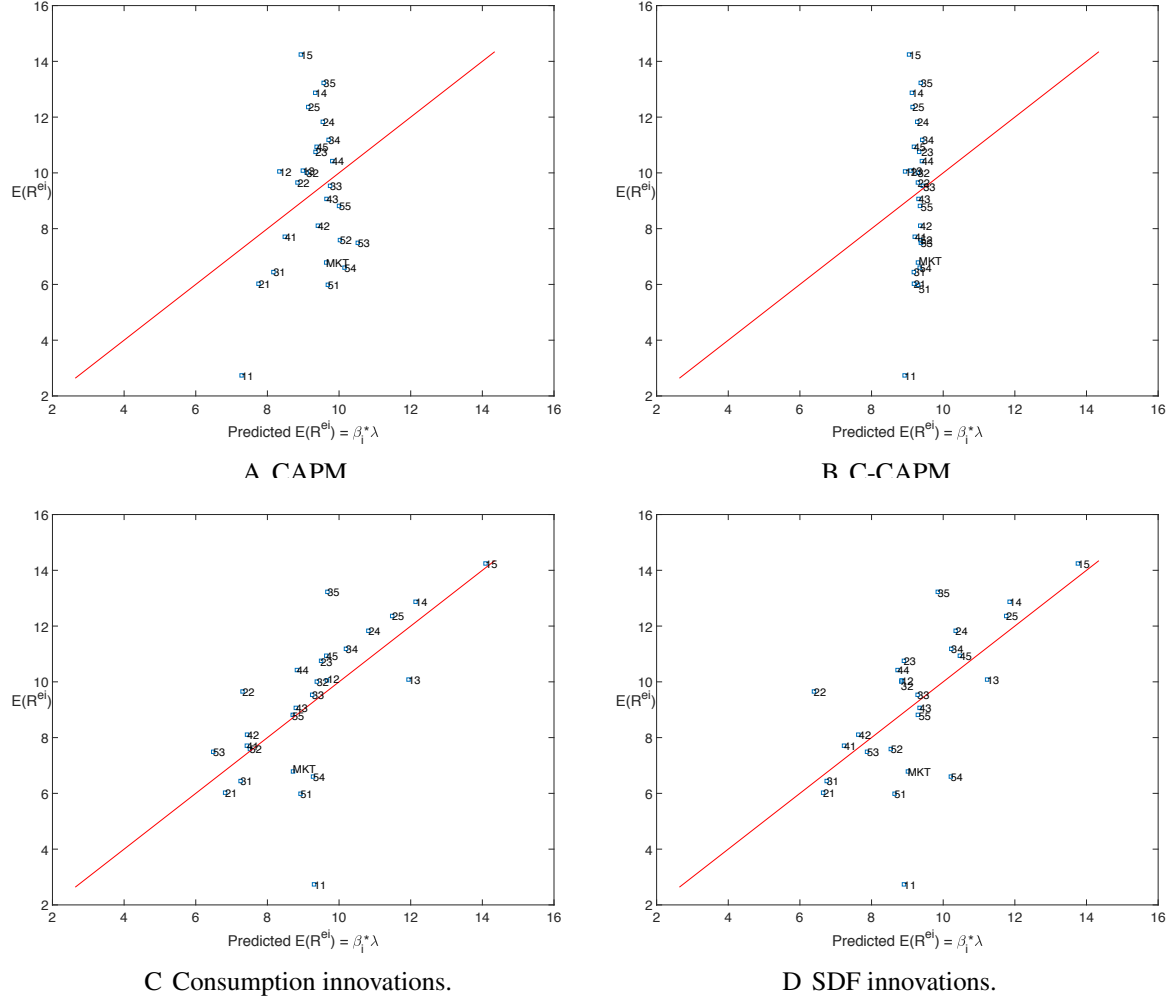
FIGURE 1: **Autocorrelation Functions:** This figure plots the autocorrelation coefficients at horizons up to 20 quarters for output, consumption, investment, inflation, the Federal Funds rate, and the 5-year Treasury yield both in the data (red dashed line) and in the baseline model (blue solid line). The blue shaded areas correspond to 95% confidence bands of model-implied autocorrelations taking into account 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 theoretic results combine the responses to the three news shocks in the model (1Q, 4Q, and 8Q news shocks) with assigning a weight of  $\sigma_{XQ}^2 / (\sigma_{1Q}^2 + \sigma_{4Q}^2 + \sigma_{8Q}^2)$  to the X-quarter news response. The theoretic 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 theoretic results combine the responses to the three news shocks in the model (1Q, 4Q, and 8Q news shocks) with assigning a weight of  $\sigma_{XQ}^2 / (\sigma_{1Q}^2 + \sigma_{4Q}^2 + \sigma_{8Q}^2)$  to the X-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.



**FIGURE 4: Realized vs. Fitted Expected Returns:** The figure shows the pricing errors for each of the 25 Fama-French portfolios for the four one-factor models. In panel A the factor is the CAPM market return; in panel B – C-CAPM consumption growth; panel C – innovations in consumption implied by our model with news shocks (where we zeroed monetary shocks); panel D – innovations in the recursive SDF implied by our model with news shocks. Each two-digit number represents one portfolio. The first digit refers to the size quintiles (1 indicating the smallest firms, 5 the largest), and 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 generated using the Fama-MacBeth regressions in Table 4 and A.1.

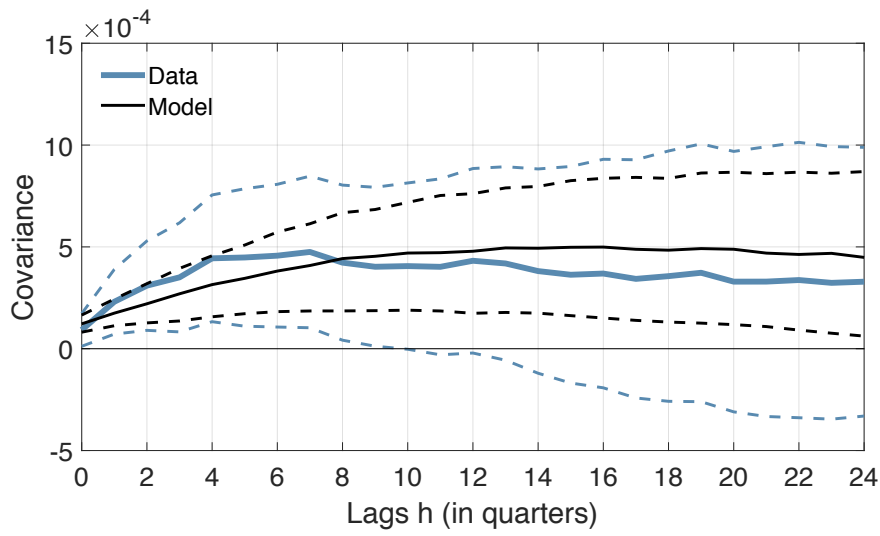
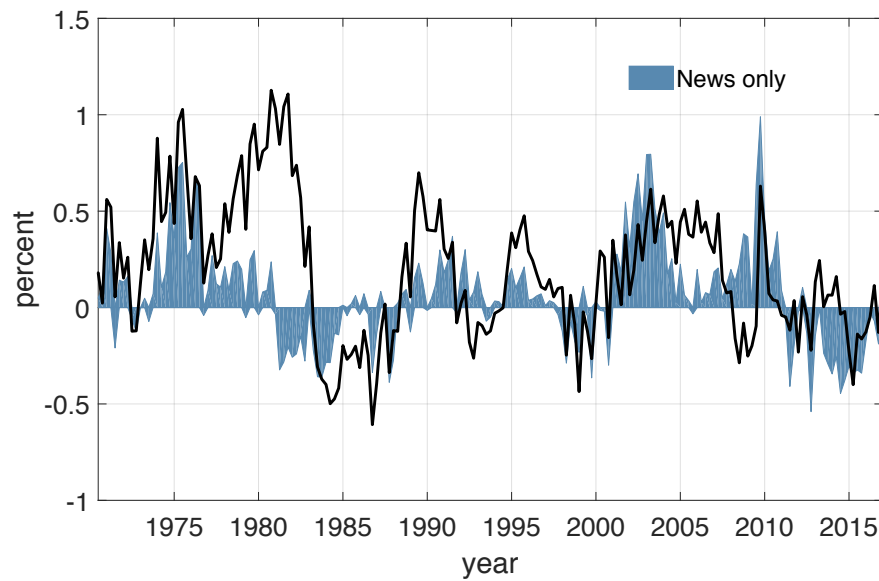
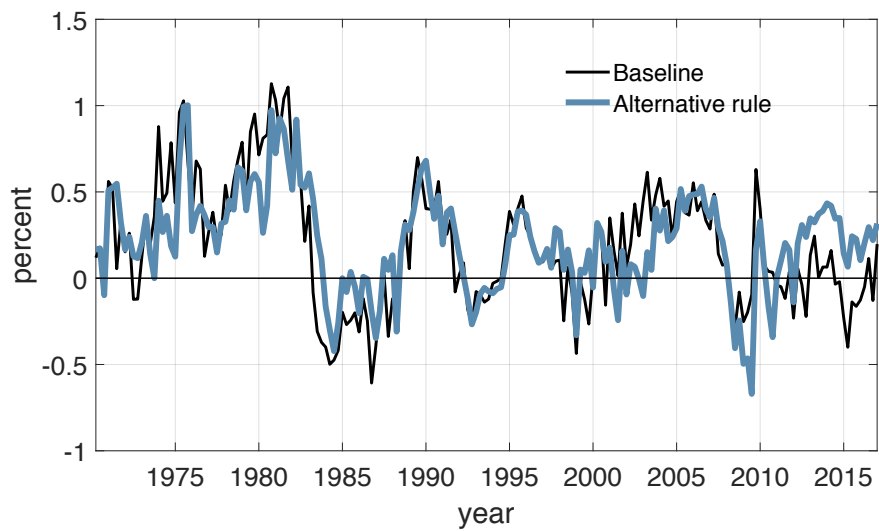


FIGURE 5: **Consumption Growth Predictability:** The figure plots the covariance of consumption growth  $c_{t+1+h} - c_t$  and market return  $r_{t,t+1}$  both in the data (thick blue line) and the model (thin black line). The empirical sample consists of quarterly data from 1970:1 to 2016:2. Corresponding 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.



A The role of news



B Alternative monetary policy rule

**FIGURE 6: Natural vs. Actual Rate of Interest:** This figure shows the difference between the natural and the actual real interest rates,  $r^* - r$ . Panel A shows the history of  $r^* - r$  implied by the model with all shocks (black line) and with news shocks only (blue area). Panel B shows the history of  $r^* - r$  implied by the baseline model (thin black line) and a model with a forward-looking monetary policy rule (thick blue line) as specified in Equation 23. The correlation between the two series in Panel B is 0.77. The figure shows the corresponding median values across the 5'000 shock series resulting from the particle filter.

## A Appendix

### A.1 Equilibrium conditions

Together with the exogenously given (1), (7), (8), (13)-(14), equilibrium is characterised by the following conditions:

$$\begin{aligned}
V_t &= \frac{C_t^{1-1/\psi}}{1 - \frac{1}{\psi}} - \eta_0 \frac{A_t^{1-1/\psi} L_t^{1+1/\eta}}{1 + \frac{1}{\eta}} + \beta \left[ E_t \left[ V_{t+1}^\gamma \right] \right]^{\frac{1}{\gamma}}, \\
E_t \left[ M_{t,t+1} \Pi_{t+1}^{-1} R_{n,t} \right] &= 1, \\
E_t \left[ M_{t+1} \frac{\Xi_{t+1} \alpha Z_t \left( \frac{A_{t+1} L_{t+1}}{K_{t+1}} \right)^{1-\alpha} + Q_{t+1} \left( 1 - \delta + \zeta_1 (1 - \zeta) \left( \frac{I_{t+1}}{K_{t+1}} \right)^\zeta + \zeta_2 \right)}{Q_t} \right] &= 1, \\
W_t &= \Xi_t (1 - \alpha) Z_t A_t^{1-\alpha} K_t^\alpha L_t^{-\alpha}, \\
\Pi_{o,t} &= \frac{\varepsilon}{\varepsilon - 1} \frac{\Phi_{1,t}}{\Phi_{2,t}}, \\
\Phi_{1,t} &= \Pi_t \left[ \Xi_t Y_t + \theta \Pi^{-\varepsilon} E_t \left[ M_{t,t+1} \Pi_{t+1}^{\varepsilon-1} \Phi_{1,t+1} \right] \right], \\
\Phi_{2,t} &= Y_t + \theta \Pi^{1-\varepsilon} E_t \left[ M_{t,t+1} \Pi_{t+1}^{\varepsilon-1} \Phi_{2,t+1} \right], \\
\Pi_t^{1-\varepsilon} &= (1 - \theta) \Pi_{o,t}^{1-\varepsilon} + \theta \Pi^{1-\varepsilon}, \\
\Delta_t &= \Pi_t^\varepsilon \left[ (1 - \theta) \Pi_{o,t}^{-\varepsilon} + \theta \Pi^{-\varepsilon} \Delta_{t-1} \right], \\
\Delta_t Y_t &= Z_t (A_t L_t)^{1-\alpha} K_t^\alpha, \\
Y_t &= C_t + I_t,
\end{aligned}$$

where

$$\begin{aligned}
Q_t &= \frac{1}{\zeta_1 \zeta} \left[ \frac{I_t}{K_t} \right]^{1-\zeta}, \\
M_{t,t+1} &= \beta \left[ \frac{V_{t+1}}{E_t \left[ V_{t+1}^\gamma \right]} \right]^{\gamma-1} \left[ \frac{C_{t+1}}{C_t} \right]^{-1/\psi}.
\end{aligned}$$

Moreover, (1) can be easily rewritten as a first order autoregressive system. For simplicity of the presentation, consider the case with four-quarter news only:

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

can be rewritten as

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

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

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

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

## A.2 Data used in Model Estimation

Our data sample is from 1970:Q1 to 2014:Q2. 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 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 [Kurmman 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.4 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.5 Robustness: Filtering of Structural Shocks

Figure [A.1](#) shows robustness results for the filtered shocks both for variations in the considered sample period as well as the number and identity of observables. Panel A of figure [A.1](#) shows that by employing a sample from 1970:Q1 to 2007:Q2, i.e. excluding the zero lower bound period, the resulting difference between  $r$  and  $r^*$  turns out identical to that obtained with the baseline sample that ends in 2016:Q4. When instead the sample is shortened at the beginning, 1984:Q1 to 2016:Q4, the filtered difference between  $r$  and  $r^*$  is no longer identical, but it continues to be highly correlated (correlation coefficient is equal to 0.68) with our baseline specification. This difference can be partly attributed to a smaller sample delivering a noisier filtered series. However this result is also in line with the recent finding by [Gambetti et al. \(2017\)](#) who document systematic differences in the response of short- and long-term interest rates to news shocks in TFP before and after 1980.

Panel B of figure [A.1](#), in turn, compares the results for different sets of observables. Again, the results are largely robust to changing their number and identity. The correlations coefficients of the baseline specification that includes five observables with the other specifications are high: 0.80 for three observables (nominal 1-quarter Treasury yield, quarterly inflation, and real stock market return); 0.75 for four observables (HP-filtered real GDP, nominal 1-quarter Treasury yield, quarterly inflation, and real stock market return); and 0.87 for six observables (HP-filtered real consumption and GDP, nominal 1-quarter Treasury yield, the nominal 10-year minus 1-quarter Treasury yield spread, quarterly inflation, and real stock market return).

## A.6 First-Pass Estimates of Betas

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

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

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 zero. We compute standard errors using standard system OLS as well as GMM-based procedures. Using either approach, the table below indicates that, at conventional significance levels, one can reject the hypotheses that  $\beta_{ij} = \beta_j, \forall i$  (Panel A) and  $\beta_{ij} = 0, \forall i$  (Panel B) for each factor:

| Panel A: Tests for no spread ( <i>p</i> -values)     |             |       |
|------------------------------------------------------|-------------|-------|
|                                                      | Consumption | SDF   |
| OLS                                                  | 0.000       | 0.001 |
| GMM                                                  | 0.000       | 0.000 |
| Panel B: Joint tests versus zero ( <i>p</i> -values) |             |       |
|                                                      | Consumption | SDF   |
| OLS                                                  | 0.002       | 0.001 |
| GMM                                                  | 0.001       | 0.000 |

## A.7 Comparison with Parker and Julliard (2005)

We investigate whether the macro factor (consumption or SDF) filtered from our news model makes an incremental contribution to the model's overall explanatory power, given the presence of the [Parker and Julliard \(2005\)](#) ultimate consumption growth risk. To this end we run cross-sectional regressions with simple regression betas (equivalently, asset covariances with the factors) as the explanatory variables. Hence Panel B of Table 5 displays the prices of covariance risk rather than risk premia.

[Parker and Julliard \(2005\)](#) argue that the risk to consumption is better measured by the response of consumption to a return over a long horizon, as given by

$$\beta_{i,S} = \frac{\text{Cov}\left[\ln\left(\frac{C_{t+1+S}}{C_t}\right), R_{i,t+1}\right]}{\text{Var}\left(\ln\left(\frac{C_{t+1+S}}{C_t}\right)\right)}$$

We follow [Parker and Julliard \(2005\)](#) and pick  $S = 11$  quarters.

Panel B of Table A.1 replicates [Parker and Julliard \(2005\)](#) in our sample which spans 1970 – 2013 (due to compounding of the ultimate consumption we loose three years of observations compared to the analysis in Table 4). We confirm the original results in [Parker and Julliard \(2005\)](#): a slow moving three-year consumption growth perform better compared, for instance, with the simple one-quarter consumption growth in Panel A of Table A.1. The main difference is that there is substantial uncertainty in the risk price estimates.

Panel B of Table 5 shows the results of a multi-factor model that includes consumption filtered from our news model along with the ultimate consumption growth. Results for the prices of covariance risk imply that a news-based consumption innovation has explanatory power for the cross-section of expected returns above and beyond the ultimate consumption series. Indeed, the price of covariance risk associated with our news-based consumption innovation series stays statistically significant in a regression with a constant. On the contrary the price of risk for ultimate consumption more than halves, and falls in the insignificant territory. Moreover, when moving from Panel A to Panel B we observe an increase in cross-sectional  $R^2$ , and a decrease in its variability.

Overall the evidence points to the ability of a model with news shocks to identify (macro) factors that improve the explanatory power of the expected return model after controlling for slow adjustment in consumption.

## A.8 Additional Tables

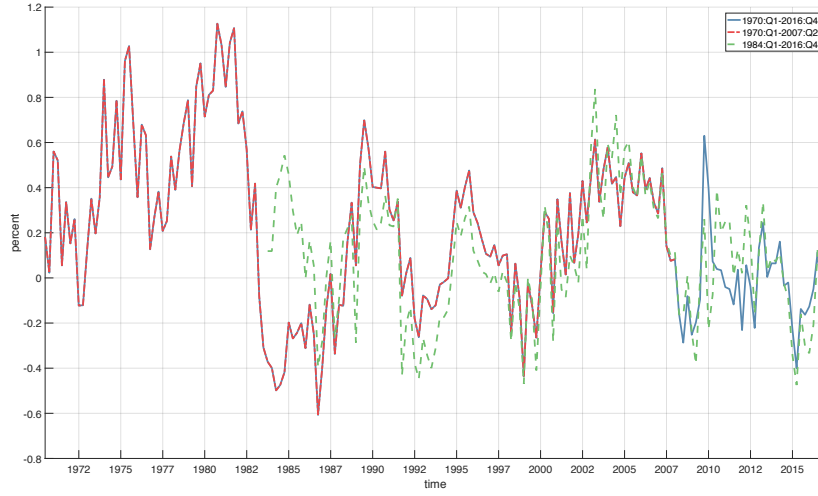
TABLE A.1: **Benchmark Cross-Sectional Results.** We estimate cross-sectional regressions with and without a constant. In particular, the table reports results from running the cross-sectional regression

$$\overline{R}_i^e = (\gamma) + \beta_i \lambda + \alpha_i,$$

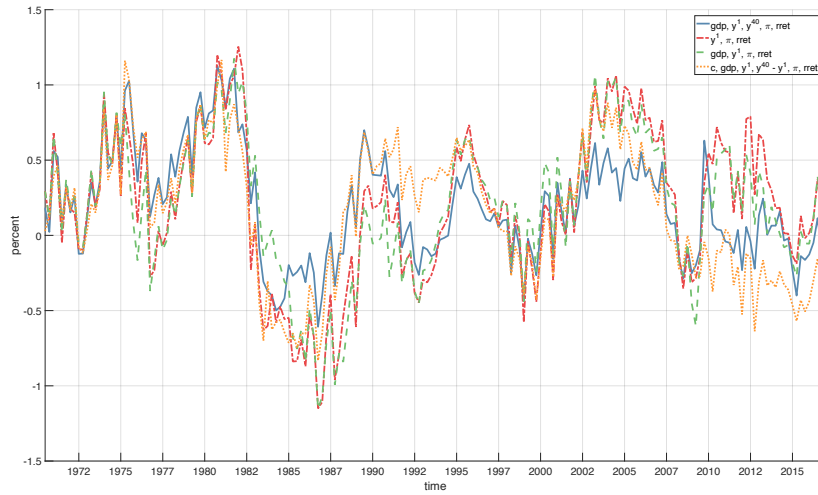
where  $\overline{R}_i^e$  is the mean excess return of portfolio  $i$  and  $\beta_i$  is the vector of factor betas of portfolio  $i$  estimated in the first-pass regression. The models are estimated using quarterly excess returns on the 25 Fama-French size and book-to-market ranked portfolios. The 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, for the model with the constant, 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.

| Panel A: CAPM and C-CAPM                                 |                              |                                    |       |       |                  |                |
|----------------------------------------------------------|------------------------------|------------------------------------|-------|-------|------------------|----------------|
| Constant                                                 | $\lambda_C$                  | $\lambda_{MKT}$                    | RMSE  | MAPE  | Joint $p$ -value | $R^2$          |
|                                                          |                              | <b>0.020</b><br>(0.007)<br>{0.007} | 3.341 | 2.524 | 0.000            | -0.64          |
| <b>0.034</b><br>(0.011)<br>{0.011}                       |                              | -0.010<br>(0.012)<br>{0.012}       | 2.501 | 2.125 | 0.000            | 0.08<br>(0.19) |
|                                                          | 0.006<br>(0.002)<br>{0.004}  |                                    | 3.274 | 2.540 | 0.000            | -0.58          |
| <b>0.025</b><br>(0.007)<br>{0.008}                       | -0.000<br>(0.002)<br>{0.002} |                                    | 2.604 | 2.141 | 0.000            | 0.00<br>(0.06) |
|                                                          | 0.004<br>(0.002)<br>{0.003}  | <b>0.021</b><br>(0.007)<br>{0.007} | 3.249 | 2.495 | 0.000            | -0.55          |
| <b>0.034</b><br>(0.011)<br>{0.012}                       | 0.003<br>(0.002)<br>{0.003}  | -0.010<br>(0.012)<br>{0.013}       | 2.413 | 1.989 | 0.000            | 0.14<br>(0.39) |
| Panel B: Parker and Julliard (2005) ultimate consumption |                              |                                    |       |       |                  |                |
| Constant                                                 | $\lambda_{PJ}$               |                                    | RMSE  | MAPE  | Joint $p$ -value | $R^2$          |
|                                                          | 0.044<br>(0.014)<br>{0.028}  |                                    | 2.290 | 1.862 | 0.000            | 0.27           |
| 0.008<br>(0.009)<br>{0.011}                              | 0.029<br>(0.010)<br>{0.018}  |                                    | 2.105 | 1.685 | 0.000            | 0.39<br>(0.30) |

## A.9 Additional Figures



A Different sample periods.



B Different observables.

FIGURE A.1: **Shock Filtering Robustness:** This figure plots the difference between the natural and the actual real interest rates,  $r^* - r$  when we vary the sample period (Panel A) or the set of observables (Panel B) in the structural shock filtering. The graphs show the median values across the 5'000 shock series resulting from the particle filter.

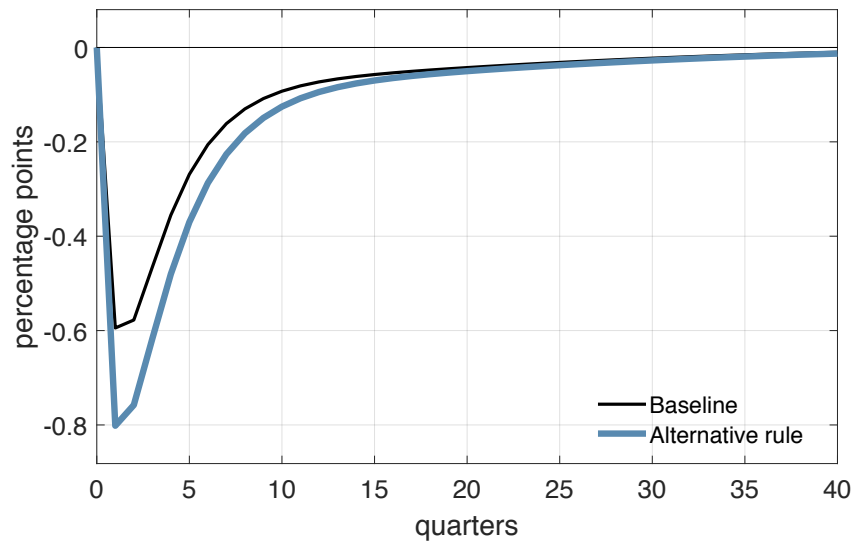


FIGURE A.2: **Inflation IRF under Alternative Monetary Policy Rules:** The figure plots the impulse responses of inflation to a one standard deviation one-quarter news shock in the baseline model and a model with a forward-looking monetary policy rule as specified in Equation 23.