# News Shocks and Asset Prices

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**Abstract**

We examine the role of expectation, or news, shocks for asset prices. 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 bond returns. Further, anticipated changes in future productivity growth translate into fluctuations in the natural rate of interest, which we show to have important implications for the conduct of monetary policy.

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# 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.[1] 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 both the qualitative and quantitative implications of accounting for this latent information for the natural rate of interest and macroeconomic risk in the economy.

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 find 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 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. productivity shocks 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.[2] By definition, news are information available to agents

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

[2] 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

that is not yet reflected in the production possibilities of the economy. This makes the identification in the data not trivial. Theoretical restrictions imposed by the structural model on the responses of forward-looking 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.[3]

The estimated model matches salient macroeconomic and asset pricing moments. Further, model-implied responses of endogenous variables to news shocks mimic those identified in an empirical VAR. At the same time, our model allows for a richer information structure that differentiates between news at different horizons, highlighting the advantages 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 sizeable fraction of business cycle fluctuations. In particular, news are an important determinant of the expected consumption path and, hence, consumption innovations. Indeed, in the estimated model, news shocks account for one quarter of the variability in consumption innovations. Finally, using the equivalent rep-

structures, "noise" and "news", are observationally equivalent. In the rest of the paper we take a news perspective.

[3]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 knows 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.

resentation of our model proposed by Chahrour and Jurado (2018), we find that the variation in macroeconomic and financial variables is primarily due to true information about the fundamentals rather than pure beliefs.

Having established the importance of news for macro-finance fluctuations, we consider 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 equity returns and the price dividend ratio. We therefore investigate the pricing ability of innovations in consumption filtered from our news-driven 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 proxy for consumption innovations with the first differences or the residual from a simple time series regression. In addition, our news-driven pricing model is able to simultaneously price stocks and bonds. Cross-sectional regressions on one-, four-, and eight-quarters news filtered from our model confirm that different assets are informative for different news shock horizons. While bond returns are mainly exposed to one-quarter news, value-growth 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, news-induced fluctuations in expected consumption translate into large fluctuations in the natural rate of interest, defined as the real short rate that would have prevailed in the absence of nominal rigidities. Moreover, news shocks explain a significant fraction of the variation in the gap between the natural rate and the actual real rate, a measure of monetary policy stance. 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 inflation. 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. We use the model to carry out a historical decomposition of the variation in the gap between the natural and the real short rate. 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.

Our paper is related to Beaudry and Portier (2006) and Kurmann and Otrok (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), and Forni, Gambetti, Lippi and Sala (2017).

Our modelling 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 information structure embedded in our model delivers a new perspective on the long run-risk strand in consumption-based asset pricing literature dating back to Bansal and Yaron (2004) work. Indeed, 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). Inspired by Schmitt-Grohe and Uribe (2012), we consider large changes in expectations at business cycle horizon.

Our paper is also 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.

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:

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

where $\varepsilon_{0,t}$ are date $t$ productivity surprises, while innovations $\varepsilon_{j,t-j}$ are anticipated $j$ periods ahead: they affect date-$t$ productivity, but are period $t-j$ information.[4] 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 shock, as shown in Chahrour and Jurado (2018). This equivalent information structure can be formally represented as

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

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

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

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

where $\nu_{j,t-j}$ is the noise component of the signal $s_{j,t-j}$ received $j$ periods ahead of the realization of the productivity shock $\varepsilon_t$.[5]

The rest of the model is a version of the standard New-Keynesian framework.[6]

*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

[4]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.

[5]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 et al. (2016).

[6]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.

investment in capital $I_t$ to maximize her lifetime utility $U_t$ defined recursively[7]

$$U_t = \frac{C_t^{1-1/\psi}}{1-\frac{1}{\psi}} - \eta_0 \frac{A_t^{1-1/\psi} L_t^{1+1/\eta}}{1+\frac{1}{\eta}} + \beta \left[ \mathrm{E}_t \left[ U_{t+1}^{\gamma} \right] \right]^{\frac{1}{\gamma}}, \tag{6}$$

subject to:

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

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

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

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

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

subject to

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

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

[7] 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.

where the aggregate price index $P_t$ is given by

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

The expression in (9) represents the expected profits during the time 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 $P_{o,t}Y_t(j)$ 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

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

The demand functions for firms' output is given by (11), where $\epsilon$ 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

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

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 $u_{m,t}$ is a monetary policy shock

$$u_{m,t} = \rho_m u_{m,t-1} + \varepsilon_{m,t}. \tag{15}$$

Adding to the standard Taylor rule, (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 policymaking.

*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 (1), (7), (8), (13)-(15), equilibrium is characterised by the set of conditions presented in Appendix A.1. The Appendix also shows that the specification of news in (1) can be rewritten state-space form, making the model amendable to standard solution methods.

## 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.[8] 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 et al. (2017). Intuitively, pruning means omitting terms of higher-order than the considered approximation order when the system is iterated forward in time.[9] 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,

[8]For example, a first-order approximation of the model is not able to generate a positive slope in the term structure of interest rates.

[9]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 fifth-order approximations.

$\Delta y_t$; 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 price-dividend ratio, $PD_t$. Further details about the data are deferred to Appendix A.2. The GMM estimation relies on the mean, the variance, the contemporaneous covariances and the first auto-covariances in the data as moments. Hence, we let

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

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

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

Here, $W$ is a positive definite weighting matrix and $E\left[q_t(\theta)\right]$ contains the model-implied moments. We use the conventional two-step implementation of GMM by letting $W_T = \text{diag}\left(\hat{S}^{-1}\right)$ 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 $W_T = \text{diag}\left(\hat{S}^{-1}_{\hat{\theta}^{\text{step 1}}}\right)$, where $\hat{S}_{\hat{\theta}^{\text{step 1}}}$ denotes the long-run variance of our moments re-centered around $E\left[q_t\left(\widehat{\theta^{\text{step 1}}}\right)\right]$. The long-run variances in both steps are estimated by the Newey-West estimator using 10 lags, but our results are robust to using more lags.

*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: HP-filtered 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 identify structural shocks from a 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 4.2 below.

# 3 Estimation Results

This section presents our main results in terms of parameter estimates, moments generated by the model, variance decomposition, and impulse responses of 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 $Leverage = 3$, 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 Kiley and Sim (2017) and the intuition that 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 the 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, for instance, Bansal and Yaron (2004), where the predictable component of economic fundamentals is small and highly persistent.

Our estimate for the elasticity of intertemporal substitution (EIS) $\psi = 1.65$ is greater than one, in line with the values used in the long-run risk literature. See, for instance, Bansal and Yaron (2004) and Kaltenbrunner and Lochstoer (2010). With a high EIS, agents respond to expected productivity improvements with only small immediate increases in consumption. If instead the elasticity was low, agents immediately adjust their consumption to anticipated increases in productivity which results in counterfactually low or negative correlation between asset valuation 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. Andreasen and Jorgensen (2018) argue that, additionally taking into account the agents attitude towards the timing of risk, effective risk aversion is even lower. Importantly, the parameter $\gamma$ does not have a significant effect on the dynamics of macroeconomic variables, even at higher orders (see also Tallarini (2000)).

*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 short-rate and 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. Hence, lowering inflation variability induces too low yield volatilities, in particular, for longer term maturities. Another well known challenge is matching the volatility of the PD ratio which is between 42% and 72% of that in the data. However, these numbers represent no small accomplishment, since most models need stochastic volatility to generate volatile prices.[10]

Finally, our economy also reproduces well the empirical autocorrelation func-

[10] 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).

tions 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.* In Table 3 we decompose the variability of endogenous model variables. The first row recovers the benchmark specification with all structural shocks being active. As a result, the reported standard deviations are identical to Table 2. The following rows document corresponding results when we consecutively set the realizations of all but one shock to zero. First, news shocks to productivity generate substantial fluctuations in consumption. In fact, they account for around 51(=0.6/1.17) percent of the observed variability in consumption. Hence, news about future productivity are an important determinant of the path of expected consumption. We will revisit this point in Section 4.1 when we relate news shocks to the stochastic discount factor. Second, news shocks are the key drivers of (business cycle) fluctuations in equity returns, the real rate, and in a second instance, the price dividend ratio. They are responsible for 81(= 11.59/14.24), 69(0.48/0.7) and 39(=4.93/12.68) percent of the variance of returns, the 2-year real rate, and the price-dividend, respectively. We will further discuss the link between news and asset prices in Section 4.3 and Section 4.2. Finally, news shocks explain a substantial fraction of inflation movements.

**[Insert Tables 3 and 4 about here]**

*Impulse responses.* Next we turn to the analysis of the dynamics of model quantities and prices. To this end, we compare impulse responses to a news shock in the data to those implied by our model. To identify news shocks 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. More details about data and identification procedure are discussed in Appendix A.3.

Figure 2 shows 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.[11] In particular, 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 Figure 2 about here**]

In general, 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-dividend ratio. In particular, in the data the stock price-dividend jumps up to a level between 1 and 4% above its preshock value, and returns to it after about two years. The model replicates well these price dynamics.

Only one difference stands out between model and data impulse responses, namely the response of adjusted TFP: The bottom right panel 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). However, we show in Appendix A.3 that employing the identification of Kurmann

[11] Figures A.4–A.6 display the model responses to each news shock separately.

and Sims (2017) results in data and model-implied responses of adjusted TFP that lie almost on top of each other. Importantly, changing the identification does not alter any of the other responses in the data.

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

# 4 Applications

In this section we explore the implications of news shocks for interest rates, equity prices and the macroeconomic risk in the economy.

## 4.1 News and the stochastic discount factor

Given the observed path of the economy, allowing for latent information available to agents through anticipated shocks changes the decomposition of the representative household's (log) stochastic discount factor $m_{t,t+1}$ into the expected component $\mathrm{E}_t[m_{t,t+1}]$ and the innovation $m_{t,t+1} - \mathrm{E}_t[m_{t,t+1}]$. 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, in turn, changes the innovation term. This insight is not specific to our macroeconomic model. Instead, the model simply allows us to infer the information received by agents using multiple observed variables together with theoretical restrictions on their dynamics. In this sense, our estimated model sheds new light on the factors driving asset prices.

The decomposition of the stochastic discount factor has an effect on both interest rates and risk premia. For the return $R_{i,t+1}$ on any asset $i$, including the risk-free rate of return $R_{f,t}$, we have

$$\mathrm{E}_t\left[M_{t,t+1}R_{i,t+1}\right] = 1, \tag{16}$$

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

$$M_{t,t+1} = \beta\left[\frac{V_{t+1}}{\mathrm{E}_t\left[V_{t+1}^{\gamma}\right]}\right]^{\gamma-1}\left[\frac{C_{t+1}}{C_t}\right]^{-1/\psi}, \tag{17}$$

and $V_t$ is the value function associated with household's maximization problem. More clear intuition can be gained from the approximation of Eq. (16) obtained assuming log-normality. Denoting the logs of variables with lowercase letters and the log real risk-free rate by $r_{f,t}$, we have

$$r_{f,t} + \frac{1}{2}\mathrm{Var}_t\left[m_{t,t+1}\right] = -\mathrm{E}_t\left[m_{t,t+1}\right], \tag{18}$$

$$\mathrm{E}_t\left[r_{i,t+1} - r_{f,t}\right] + \frac{1}{2}\mathrm{Var}_t\left[r_{i,t+1}\right] = -\mathrm{Cov}_t\left[m_{t,t+1}, r_{i,t+1}\right]. \tag{19}$$

Eq. (18) says that the expected component of the stochastic discount factor $\mathrm{E}_t\left[m_{t,t+1}\right]$ determines the real short-term interest rate. In turn, Eq. (19) says that the innovations in the stochastic discount factor $m_{t,t+1} - \mathrm{E}_t\left[m_{t,t+1}\right]$ represent the aggregate risk in the economy: covariance with these innovations determine assets' expected returns.[12] We will consider the effect of news on the cross-section of expected returns and interest rates in sequence.

## 4.2 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.

[12] The variance terms in (18) and (19) are Jensen's inequality adjustments.

To begin, we consider two standard benchmarks: the static CAPM of Sharpe (1964) and Lintner (1965), and the unconditional consumption CAPM (CCAPM) of Breeden (1979). The CAPM cross-sectional specification is

$$E[r^e_{i,t}] = \lambda_0 + \beta_{i,MKT}\lambda_{MKT},$$

where $E[r^e_{i,t}]$ is stock $i$ expected excess (in excess of the one-month T-bill rate from Ibbotson Associates) return and $\beta_{i,MKT}$ is stock $i$ beta with respect to the excess return on the value-weighted stock market index. In turn, the CCAPM specification is

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

where $\beta_{i,C}$ is the beta of stock $i$ with the growth rate in real per capita nondurable consumption (seasonally adjusted at annual rates) from the Bureau of Economic Analysis. As shown in Panels A and B of Table 5, neither of these two factors, despite being rooted in economic theory, has any 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 also illustrated in Panels A and B of Figure 3 which plots fitted expected against realized average returns for these portfolios.

**[Insert Table 5 about here]**

**[Insert Figure 3 about here]**

Next, we proceed to test our model-implied factors. The unconditional version of Eq. (19) can be written as

$$E[r^e_{i,t}] = \lambda_0 + \beta_{i,M}\lambda_M, \tag{21}$$

where $\beta_{i,M}$ is the beta to the innovations in the stochastic discount factor given, to the first order, by:

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

where $\varepsilon_t = \left[\varepsilon_{0,t}\,\varepsilon_{1,t}\,\varepsilon_{4,t}\,\varepsilon_{8,t}\,\varepsilon_{z,t}\,\varepsilon_{m,t}\right]'$ and $m_\varepsilon < 0$ is a vector of coefficients given by the first order approximation of the model.[13] In addition, we consider a special case of time-additive preferences that correspond to $\gamma = 1$. While the macroeconomic dynamics of the model are largely unaffected by the choice of $\gamma$, $\gamma = 1$ implies that it is only the innovations to realized consumption growth that enters the stochastic discount factor, as can be seen from (17). As a result, we have

$$\mathrm{E}[r_{i,t}^e] = \lambda_0 + \beta_{i,Cnews}\lambda_{Cnews}, \tag{22}$$

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

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

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 slightly different combinations of these shocks: the stochastic discount factor implied by recursive utility puts more weight on the longer-horizon news as current consumption reacts only moderately to changes in expected future productivity. Yet, even if the shock loadings are misspecified relative to the true stochastic discount factor, a better identification of the elementary macroeconomic shocks themselves can improve on our ability to explain the cross-section of expected returns.[14]

[13] 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. Our reported results are based on the full second-order perturbation solution.

[14] In this sense, our mechanism differs from the long-run risk models. Note, for instance, that with time-additive preferences our model is identical to CCAPM specification in (20) except for the way we measure consumption risk.

Panels C and D of Figure 3 illustrate the respective performance of the model-implied consumption innovations and stochastic discount factor innovations in explaining the average expected returns of the 25 Fama-French size and book-to-market sorted portfolios. Panels C and D of Table 5 examine the performance of these two factors more formally. When accounting for the effect of news shocks on expected consumption, innovation in consumption attains an $R^2$ of 45%. 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): despite the quite volatile $R^2$s of the news-driven model specifications, both $R^2$s are 1.6 standard deviation away from zero and clearly outperform the CAPM and CCAPM. This is a remarkable performance for a one-factor macro-based asset pricing model.

A standard concern in asset pricing models with macro factors is that the 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 Panels C and D of Table 5 are jointly significantly different from zero. We reject the hypothesis at conventional significance levels. 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 $\widehat{\lambda}$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). Panel C shows that our model-implied innovations in consumption have coefficients that are reliably positive at the 10% level, while Panel D shows that model-implied innovations in SDF are negatively priced, both in line with theoretical predictions.[15] In addition, the zero-beta rate from Panel C is not significantly larger than the risk-free rate for the consumption innovations extracted from our news model. In fact, removing the constant, leads to only a mild reduction in cross-sectional $R^2$ from 45% to 34%.

Our conclusions are robust to a range of additional tests.

To begin, Panels A of Table 6 shows that a two factor model that combines CAPM and CCAPM factors still has little explanatory power for the expected returns of 25 Fama-French size and book-to-market sorted portfolios. Panel B of Table 6 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 different horizons to represent a potentially independent sources of risk, each of them with its own risk premium:

$$E[r^e_{i,t}] = \lambda_0 + \lambda_1\beta_{i,1} + \lambda_4\beta_{i,4} + \lambda_8\beta_{i,8}, \tag{23}$$

where $\beta_{i,j}$ is the beta of returns on asset $i$ with the $j$-period anticipated news.[16] The model with three news shocks as risk factors attains an $R^2$ of 45% and a RMSE of 1.9%, a performance similar to our baseline results in Panel D of Table 5. Consistent with the intuition that positive news about future productivity decrease marginal utility, news at all horizons carry a positive risk premium.

Next, we show that news shocks are critical for our results. In untabulated results, we find that if we shut down news about productivity – keeping other

[15] 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.

[16] The news-driven models in Eqs. (21) and (22) 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. (23) 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 longer anticipation horizons for news shocks.

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 cross-sectional results are reported in Panels C and D of Table 6. The model without news performs worse than the baseline model from Panels C and D in Table 5 on several dimensions. First, comparing the respective Panels D, we observe that despite the fact that both models deliver a statistically significant risk premium, the model without news clearly has a worse fit: not only the $R^2$ decreases from 42% to 26%, but also the variability of the $R^2$ in the model without news is larger (36% compared with 27%), making it hard to distinguish the model without news from a risk-neutral benchmark that includes only a constant. Similarly, looking at respective Panels C, the pricing performance of consumption innovations filtered from the model without news is worse than that of the baseline model. For example, the premium on consumption innovations is no longer significant according to the GMM standard errors, and the sampling variability in $R^2$ increases from 29% to 33%. Second, and most importantly, the relatively good pricing ability of 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, measurement error is now used to account both for low variability of consumption innovations and large dispersion in asset prices.

**[Insert Table 6 about here]**

Finally, Table 7 shows that our results hold in alternative cross-sections of assets. Panel A of Table 7 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 42% (see Panel D in Table 5) to 38%, and the root mean squared errors (RMSE) and mean absolute pricing errors (MAPE) remain mostly unchanged (from 1.99% and 1.45% to 1.95% and 1.48%). Panel B in Table 7 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 2.4% to 1% per year. For comparison, the average pricing error to be explained is about 4.90% for our sample period and 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 findings in Panels C and D of Table 7 reinforce this latter point. For the cross-section of stock and bond returns in Panel D, the model with unrestricted news shocks delivers excellent performance - at par of the news-driven SDF in Panel B. 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 6 and Panel C of Table 7, respectively) we are able to recover a strong premium associated with long-term eight-quarters news besides that of the one-quarter news.

**[Insert Table 7 about here]**

## 4.3 Natural rate of interest

We define the natural rate of interest as the real short rate in the counterfactual economy without nominal rigidities.[17] 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 be close to optimal in richer settings (see Justiniano, Primiceri and Tambalotti (2013)). In practice, monetary policy rules typically assume a constant natural rate of interest,

[17] 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).

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.[18]

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 $r^*$ 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 understand the contribution of news, note that, to the first order, (17) and (18) imply

$$r_t^* \approx \frac{1}{\psi} \mathrm{E}_t \left( c_{t+1}^* - c_t^* \right) + \text{constant},$$

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 4 plots the history of $r_t^* - r_t$ implied by the model. As shown in Panel B 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.

[18] 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.

**[Insert Figure 4 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.[19] 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 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.[20]

To see why news shocks lead to deviations between $r_t^*$ and $r_t$, compare their responses to positive news about future productivity. On 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,

[19] See, for instance, Taylor (2009).

[20] 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.

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 monetary policy rules should take into account the time-varying natural rate, and in particular its component 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. Other forward-looking variables may not capture news shocks well. For instance, expected future inflation, which enters the monetary policy rule in Clarida et al. (2000), falls in response to positive productivity growth news, as can be seen in Figure 2. Interestingly, the rationale for including financial variables in the monetary policy rule does not not rely on financial frictions, unlike in the recent policy discussion.[21] Instead, it stems from the informativeness of asset prices about news shocks that have a large effect on future economic conditions but only a limited effect contemporaneously.

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.[22] 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.[23]

[21] See, for instance, Borio (2014) and Stein (2014).

[22] See, for instance, Summers (2014) and Eggertsson, Mehrotra and Robbins (2018).

[23] 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.

# 5 Conclusion

In this paper we explore the qualitative and quantitative implications of the expectation-driven view of business cycle fluctuations.

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 the failure of consumption-based asset pricing models. 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**

| | | | | | |
|---|---|---|---|---|---|
| *Firm:* | | | *Monetary Policy:* | | |
| $\delta$ | 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 |
| *Leverage* | firm leverage | 3.000 | $\phi_{y2}$ | TR coefficient output gap | 0.080 |

**Panel B: Estimated Parameters**

| | | | | | |
|---|---|---|---|---|---|
| *Preferences:* | | | *Shocks:* | | |
| $\beta$ | time discount | 0.995 | $\mu_a$ | steady-state productivity growth | 0.401 |
| | | [0.994,0.996] | | | [0.378,0.422] |
| $\gamma$ | risk aversion | -85.000 | $\rho_a$ | AR(1) productivity | 0.360 |
| | | [-97.303,-73.301] | | | [0.312,0.395] |
| $\psi$ | IES | 1.650 | $\sigma_a$ | volatility productivity | 0.505 |
| | | [1.556,1.774] | | | [0.461,0.548] |
| $\eta$ | Frisch elasticity | 1.800 | $\sigma_{1Q}$ | volatility 1Q news | 0.498 |
| | | [1.660,1.948] | | | [0.429,0.562] |
| | | | $\sigma_{4Q}$ | volatility 4Q news | 0.501 |
| | | | | | [0.471,0.531] |
| *Firm:* | | | $\sigma_{8Q}$ | volatility 8Q news | 0.199 |
| $\epsilon$ | | 13.500 | | | [0.121,0.290] |
| | | [11.633,15.189] | $\rho_z$ | AR(1) technology | 0.975 |
| $\zeta$ | capital adjustment costs | 0.940 | | | [0.9614,0.9866] |
| | | [0.931,0.948] | $\sigma_z$ | volatility technology | 0.722 |
| | | | | | [0.663,0.781] |
| | | | $\sigma_m$ | volatility monetary policy | 0.210 |
| | | | | | [0.201,0.223] |

Table 2: **Unconditional Model 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 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 | 0.85 | 1.00 | 1.54 | 0.87 | 1.00 |
| | [2.77,3.28] | [0.84,0.86] | | | | |
| Consumption | 1.17 | 0.91 | 0.82 | 1.27 | 0.89 | 0.88 |
| | [1.10,1.29] | [0.89,0.92] | [0.75,0.86] | | | |
| Investment | 7.63 | 0.78 | 0.98 | 7.07 | 0.85 | 0.92 |
| | [7.06,8.83] | [0.77,0.80] | [0.96,0.98] | | | |
| Inflation | 1.20 | 0.87 | 0.06 | 0.61 | 0.89 | 0.11 |
| | [0.81,1.52] | [0.84,0.92] | [0.05,0.07] | | | |
| *Non-Targeted Moments:* | | | | | | |
| Wages | 0.63 | 0.92 | 0.20 | 0.93 | 0.68 | 0.09 |
| | [0.59,0.70] | [0.91,0.93] | [0.18,0.22] | | | |

**Panel B: Asset Prices**

| | Model | | | | Data | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | AR(1) | Cor(.,yt) | Mean | SD | AR(1) | Cor(.,yt) |
| *Targeted Moments:* | | | | | | | | |
| Nominal Rate 1Q | 5.61 | 3.75 | 0.92 | 0.06 | 5.62 | 3.88 | 0.94 | 0.22 |
| | [4.41,7.63] | [2.75,6.07] | [0.88,0.95] | [0.03,0.09] | | | | |
| Slope | 1.23 | 1.82 | 0.84 | -0.29 | 1.23 | 2.09 | 0.77 | -0.47 |
| | [0.84,1.98] | [1.65,2.12] | [0.81,0.85] | [-0.34,-0.25] | | | | |
| PD-Ratio | 0.02 | 12.68 | 0.97 | -0.19 | 0.06 | 24.83 | 0.93 | 0.10 |
| | [0.01,0.03] | [10.26,18.23] | [0.96,0.99] | [-0.23,-0.13] | | | | |
| *Non-Targeted Moments:* | | | | | | | | |
| Nominal 5Y | 6.62 | 2.65 | 0.96 | -0.07 | 6.34 | 3.06 | 0.97 | 0.00 |
| | [5.44,9.00] | [1.65,4.89] | [0.94,0.98] | [-0.10,-0.03] | | | | |
| Nominal 10Y | 6.84 | 2.11 | 0.98 | -0.09 | 6.84 | 2.71 | 0.97 | -0.05 |
| | [5.62,9.53] | [1.21,4.23] | [0.95,0.98] | [-0.12,-0.05] | | | | |
| Real 2Y | 1.71 | 0.70 | 0.89 | 0.04 | 1.87 | 1.80 | 0.89 | 0.10 |
| | [1.41,1.96] | [0.66,0.77] | [0.89,0.90] | [0.02,0.06] | | | | |
| Real Equity Returns | 8.23 | 14.24 | -0.04 | -0.23 | 5.66 | 36.29 | 0.07 | -0.08 |
| | [7.25,9.40] | [13.46,15.21] | [-0.04,-0.03] | [-0.21,-0.25] | | | | |

Table 3: **The Role of Structural Shocks.** This table 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 obtained from simulated model data. Analogously, Panel B reports standard deviations for model-implied asset prices. 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: 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 |

**Panel B: 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 |

Table 4: **Dissecting the Role of News Shocks - Variance Decomposition.** This table reports the variance decomposition of permanent productivity shocks into surprises and news (Panel A) and fundamental and noise (Panel B). The two panels report relative percentages of the total variance induced the corresponding shocks. The results are obtained from simulating the model from the ergodic mean for 1000 periods with a burn-in of 2000 periods.

**Panel A: 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 | 84.93 | 90.66 | 82.93 | 93.01 | 93.90 |
| Noise | 15.07 | 9.34 | 17.07 | 6.99 | 6.10 |

**Panel B: 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 | 92.49 | 98.11 | 90.05 | 92.43 | 94.56 | 99.95 |
| Noise | 7.51 | 1.89 | 9.95 | 7.57 | 5.44 | 0.05 |

Table 5: **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 $\widehat{\lambda}$ on the factors 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 (Pr. err. = 0). 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 -** $\overline{R_i^e} = (\gamma) + \beta_{i,MKT}\lambda_{MKT} + \alpha_i$

| Constant | $\lambda_{MKT}$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|
| | **0.020** | 3.341 | 2.524 | 0.000 | -0.64 |
| | (0.007) | | | | |
| | {0.007} | | | | |
| **0.034** | -0.010 | 2.501 | 2.125 | 0.000 | 0.08 |
| (0.011) | (0.012) | | | | (0.19) |
| {0.011} | {0.012} | | | | |

**Panel B: C–CAPM -** $\overline{R_i^e} = (\gamma) + \beta_{i,C}\lambda_C + \alpha_i$

| Constant | $\lambda_C$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|
| | 0.006 | 3.274 | 2.540 | 0.000 | -0.58 |
| | (0.002) | | | | |
| | {0.004} | | | | |
| **0.025** | -0.000 | 2.604 | 2.141 | 0.000 | 0.00 |
| (0.007) | (0.002) | | | | (0.06) |
| {0.008} | {0.002} | | | | |

**Panel C: Baseline Model (no monetary) -** $\overline{R_i^e} = (\gamma) + \beta_{i,C}\lambda_C + \alpha_i$

| Constant | $\lambda_C$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|
| | **0.005** | 2.125 | 1.632 | 0.000 | 0.34 |
| | (0.001) | | | | |
| | {0.002} | | | | |
| 0.008 | **0.003** | 1.930 | 1.351 | 0.000 | 0.45 |
| (0.008) | (0.001) | | | | (0.29) |
| {0.013} | {0.001} | | | | |

**Panel D: Baseline Model -** $\overline{R_i^e} = (\gamma) + \beta_{i,M}\lambda_M + \alpha_i$

| Constant | $\lambda_M$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|
| | -1.210 | 3.522 | 2.910 | 0.000 | -0.82 |
| | (0.370) | | | | |
| | {0.932} | | | | |
| 0.015 | **-0.481** | 1.990 | 1.447 | 0.000 | 0.42 |
| (0.008) | (0.162) | | | | (0.27) |
| {0.011} | {0.261} | | | | |

Table 6: **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 $\widehat{\lambda}$ on the factors 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 (Pr. err. = 0). 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: Consumption plus Market returns -** $\overline{R_i^e} = (\gamma) + \beta_{i,C}\lambda_C + \beta_{i,MKT}\lambda_{MKT} + \alpha_i$

| Constant | $\lambda_C$ | $\lambda_{MKT}$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|---|
| | 0.004 | **0.021** | 3.249 | 2.495 | 0.000 | -0.55 |
| | (0.002) | (0.007) | | | | |
| | {0.003} | {0.007} | | | | |
| **0.034** | 0.003 | -0.010 | 2.413 | 1.989 | 0.000 | 0.14 |
| (0.011) | (0.002) | (0.012) | | | | (0.39) |
| {0.012} | {0.003} | {0.013} | | | | |

**Panel B: Unrestricted News Model -** $\overline{R_i^e} = (\gamma) + \beta_{i,1Q}\lambda_{1Q} + \beta_{i,4Q}\lambda_{4Q} + \beta_{i,8Q}\lambda_{8Q} + \alpha_i$

| Constant | $\lambda_{1Q}$ | $\lambda_{4Q}$ | $\lambda_{8Q}$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|---|---|
| | **2.103** | 1.897 | **0.759** | 4.941 | 4.122 | 0.000 | -2.59 |
| | (0.694) | (0.712) | (0.227) | | | | |
| | {1.094} | {1.243} | {0.407} | | | | |
| **0.020** | **0.487** | 0.352 | **0.253** | 1.933 | 1.510 | 0.000 | 0.45 |
| (0.007) | (0.209) | (0.236) | (0.080) | | | | (0.27) |
| {0.010} | {0.235} | {0.264} | {0.082} | | | | |

**Panel C: Model without News -** $\overline{R_i^e} = (\gamma) + \beta_{i,C}\lambda_C + \alpha_i$

| Constant | $\lambda_C$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|
| | 0.005 | 2.313 | 1.699 | 0.000 | 0.21 |
| | (0.002) | | | | |
| | {0.004} | | | | |
| 0.010 | 0.003 | 2.021 | 1.446 | 0.000 | 0.40 |
| (0.008) | (0.001) | | | | (0.33) |
| {0.013} | {0.002} | | | | |

**Panel D: Model without News -** $\overline{R_i^e} = (\gamma) + \beta_{i,M}\lambda_M + \alpha_i$

| Constant | $\lambda_M$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|
| | -0.767 | 4.057 | 3.402 | 0.000 | -1.42 |
| | (0.236) | | | | |
| | {0.800} | | | | |
| **0.017** | **-0.239** | 2.242 | 1.739 | 0.000 | 0.26 |
| (0.008) | (0.089) | | | | (0.36) |
| {0.010} | {0.140} | | | | |

TABLE 7: **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 and C, 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 and D, 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. The table reports the estimates of the factor risk premia $\widehat{\lambda}$ on the factors 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 (Pr. err. = 0). 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: 25FF plus Industries Portfolio -** $\overline{R_i^e} = (\gamma) + \beta_{i,M}\lambda_M + \alpha_i$

| Constant | $\lambda_M$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|
| | -1.207 | 3.406 | 2.823 | 0.000 | -1.20 |
| | (0.373) | | | | |
| | {0.937} | | | | |
| 0.015 | **-0.462** | 1.949 | 1.481 | 0.000 | 0.38 |
| (0.008) | (0.173) | | | | (0.28) |
| {0.010} | {0.279} | | | | |

**Panel B: Bond and Stocks -** $\overline{R_i^e} = (\gamma) + \beta_{i,M}\lambda_M + \alpha_i$

| Constant | $\lambda_M$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|
| | -1.070 | 2.8346 | 2.394 | 0.000 | 0.30 |
| | (0.357) | | | | |
| | {0.943} | | | | |
| **0.008** | **-0.756** | 1.139 | 1.029 | 0.000 | 0.89 |
| (0.002) | (0.310) | | | | (0.12) |
| {0.003} | {0.449} | | | | |

**Panel C: 25FF plus Industries Portfolio -** $\overline{R_i^e} = (\gamma) + \beta_{i,1Q}\lambda_{1Q} + \beta_{i,4Q}\lambda_{4Q} + \beta_{i,8Q}\lambda_{8Q} + \alpha_i$

| Constant | $\lambda_{1Q}$ | $\lambda_{4Q}$ | $\lambda_{8Q}$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|---|---|
| | **2.186** | **2.013** | **0.814** | 4.776 | 3.990 | 0.000 | -2.70 |
| | (0.720) | (0.739) | (0.245) | | | | |
| | {1.316} | {2.401} | {0.489} | | | | |
| **0.019** | **0.470** | 0.346 | **0.241** | 1.934 | 1.526 | 0.000 | 0.39 |
| (0.007) | (0.214) | (0.234) | (0.077) | | | | (0.28) |
| {0.009} | {0.227} | {0.252} | {0.078} | | | | |

**Panel D: Bond and Stocks -** $\overline{R_i^e} = (\gamma) + \beta_{i,1Q}\lambda_{1Q} + \beta_{i,4Q}\lambda_{4Q} + \beta_{i,8Q}\lambda_{8Q} + \alpha_i$

| Constant | $\lambda_{1Q}$ | $\lambda_{4Q}$ | $\lambda_{8Q}$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|---|---|
| | **1.402** | 1.216 | -0.102 | 2.354 | 2.090 | 0.008 | 0.52 |
| | (0.620) | (0.646) | (0.143) | | | | |
| | {0.856} | {3.092} | {0.764} | | | | |
| 0.008 | **1.253** | 1.151 | 0.276 | 1.117 | 0.910 | 0.005 | 0.89 |
| (0.003) | (0.584) | (0.630) | (0.181) | | | | (0.12) |
| {0.007} | {0.757} | {1.613} | {0.459} | | | | |

Table 8: **Pricing of Fundamental and Noise Shocks.** 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 $\widehat{\lambda}$ on the factors 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 (Pr. err. = 0). 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: Noise part of News; Baseline Model (no monetary) -** $\overline{R_i^e} = (\gamma) + \beta_{i,C}\lambda_C + \alpha_i$

| Constant | $\lambda_C$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|
| | -0.001 | 9.606 | 9.202 | 0.000 | -12.56 |
| | (0.001) | | | | |
| | {0.002} | | | | |
| **0.024** | **0.002** | 2.354 | 1.733 | 0.000 | 0.19 |
| (0.008) | (0.001) | | | | (0.52) |
| {0.011} | {0.001} | | | | |

**Panel B: Noise part of News; Baseline Model -** $\overline{R_i^e} = (\gamma) + \beta_{i,M}\lambda_M + \alpha_i$

| Constant | $\lambda_M$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|
| | **-0.054** | 3.006 | 2.507 | 0.000 | -0.33 |
| | (0.018) | | | | |
| | {0.030} | | | | |
| **0.017** | -0.015 | 2.539 | 1.936 | 0.000 | 0.05 |
| (0.006) | (0.016) | | | | (0.25) |
| {0.007} | {0.017} | | | | |

**Panel C: Fundamental part of News; Baseline Model (no monetary) -** $\overline{R_i^e} = (\gamma) + \beta_{i,C}\lambda_C + \alpha_i$

| Constant | $\lambda_C$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|
| | **0.004** | 2.141 | 1.593 | 0.000 | 0.33 |
| | (0.001) | | | | |
| | {0.002} | | | | |
| 0.008 | **0.003** | 1.974 | 1.375 | 0.000 | 0.43 |
| (0.008) | (0.001) | | | | (0.32) |
| {0.013} | {0.001} | | | | |

**Panel D: Fundamental part of News; Baseline Model -** $\overline{R_i^e} = (\gamma) + \beta_{i,M}\lambda_M + \alpha_i$

| Constant | $\lambda_M$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|
| | -1.208 | 3.510 | 2.903 | 0.000 | -0.81 |
| | (0.370) | | | | |
| | {0.930} | | | | |
| 0.015 | **-0.481** | 1.992 | 1.449 | 0.000 | 0.42 |
| (0.008) | (0.166) | | | | (0.27) |
| {0.011} | {0.264} | | | | |

Table 9: **Cross-Sectional Results: Horse race with Parker and Julliard (2005).** 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 prices of covariance risk $\widehat{\lambda}$ on the factors 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 (Pr. err. = 0). 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 2013.

**Panel A: Ultimate Consumption - $\overline{R_i^e} = (\gamma) + \beta_{i,C_{PJ}} \lambda_{C_{PJ}} + \alpha_i$**

| Constant | $\lambda_{C_{PJ}}$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|
| | 0.044 | 2.290 | 1.862 | 0.000 | 0.27 |
| | (0.014) | | | | |
| | {0.028} | | | | |
| 0.008 | 0.029 | 2.105 | 1.685 | 0.000 | 0.39 |
| (0.009) | (0.010) | | | | (0.30) |
| {0.011} | {0.018} | | | | |

**Panel B: Baseline Model (no monetary) - $\overline{R_i^e} = (\gamma) + \beta_{i,C} \lambda_C + \beta_{i,C_{PJ}} \lambda_{C_{PJ}} + \alpha_i$**

| Constant | $\lambda_C$ | $\lambda_{C_{PJ}}$ | RMSE | MAPE | $H_0$ : Pr. error = 0 , $p$-value | $R^2$ |
|---|---|---|---|---|---|---|
| | 0.003 | 0.017 | 2.137 | 1.616 | 0.000 | 0.37 |
| | (0.001) | (0.011) | | | | |
| | {0.002} | {0.017} | | | | |
| 0.007 | **0.002** | 0.010 | 2.009 | 1.496 | 0.000 | 0.44 |
| (0.009) | (0.001) | (0.012) | | | | (0.23) |
| {0.011} | {0.001} | {0.016} | | | | |

# 7 Figures

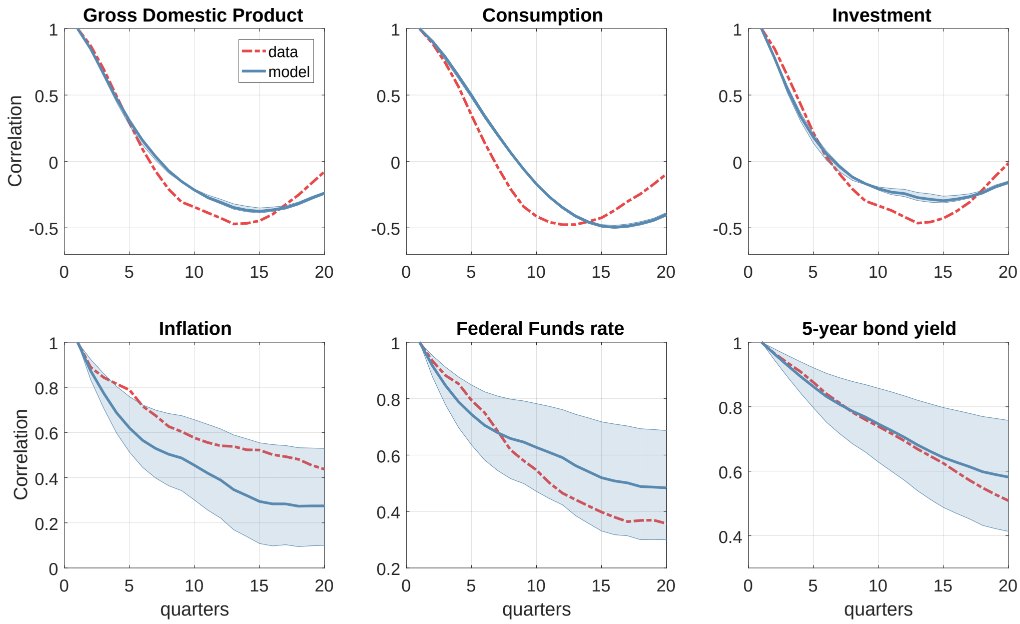



FIGURE 1: **Autocorrelation Functions**: This figure plots the autocorrelation coefficients at horizons up to 20 quarters for output, consumption, investment, inflation, the Federal Funds rate, and the 5-year Treasury yield both in the data (red dashed line) and in the baseline model (blue solid line).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

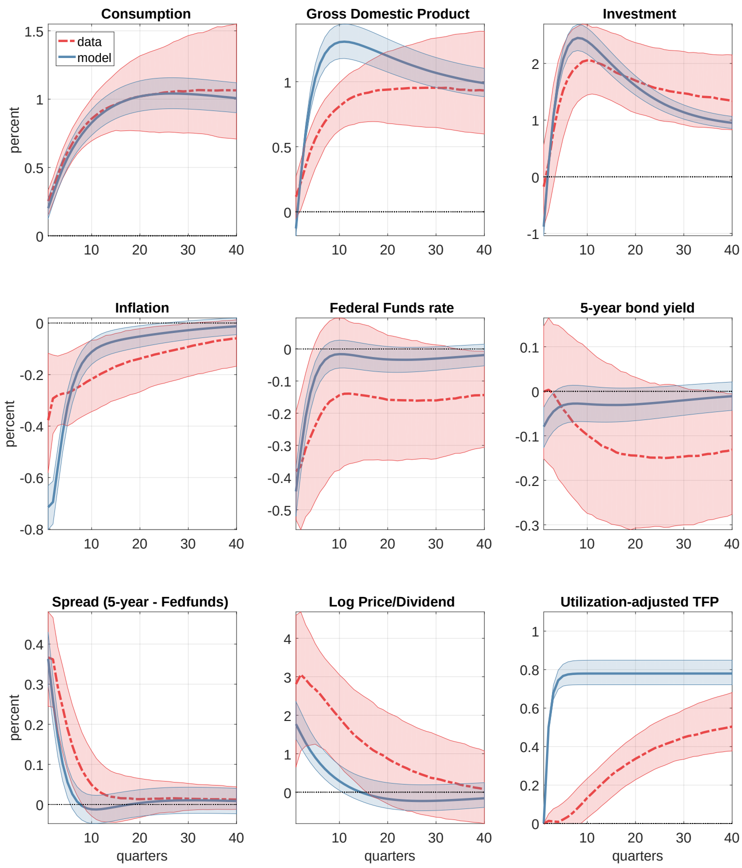
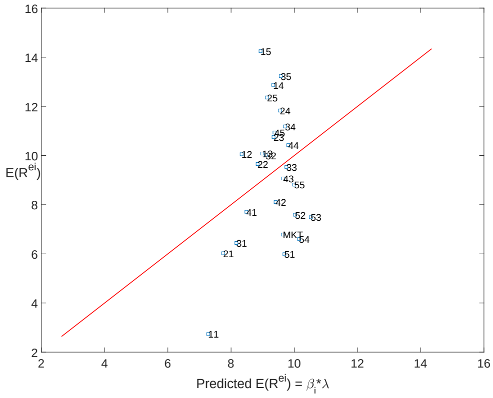
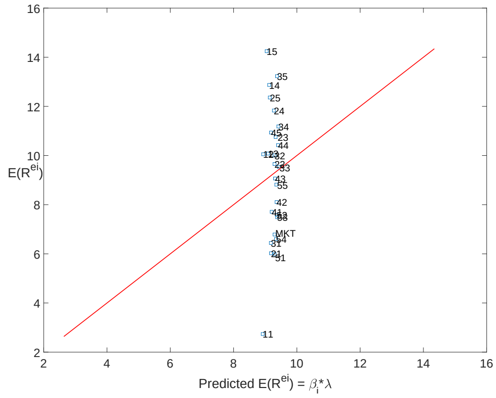


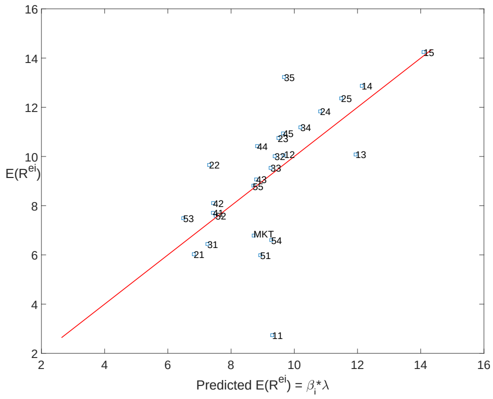

FIGURE 2: **Impulse Responses to News Shocks**: This figure plots the impulse response functions of consumption, output, investment, inflation, the Federal Funds rate, 5-year Treasury yield, the slope of the yield curve, the log price-dividend ratio and total factor productivity to a news shock both 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 $\sigma^2_{XQ}/(\sigma^2_{1Q} + \sigma^2_{4Q} + \sigma^2_{8Q})$ 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 the news shock are identified over the 0-80 quarter horizon as in Barsky and Sims (2011) and Kurmann and Otrok (2013). Figure A.1 in the appendix plots the model-implied responses to a 1-quarter news shock only along the data responses.



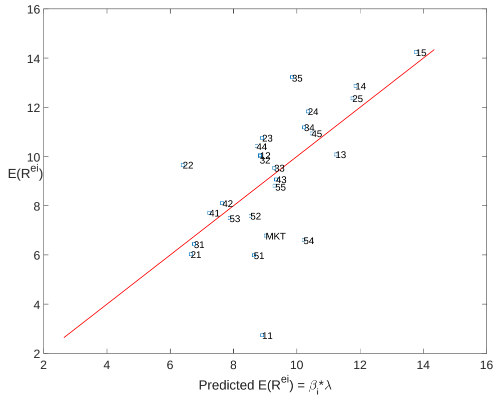

(a) CAPM.




(b) C-CAPM.




(c) Consumption Innovations.




(d) SDF Innovations.

FIGURE 3: **Realized vs. Fitted Returns**: a, CAPM; b, C-CAPM; c, Innovations in consumption from our News model (where we zeroed monetary shocks); d, Innovations in the SDF from our News model. The figure shows the pricing errors for each of the 25 Fama-French portfolios for the four models. 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 5 below.

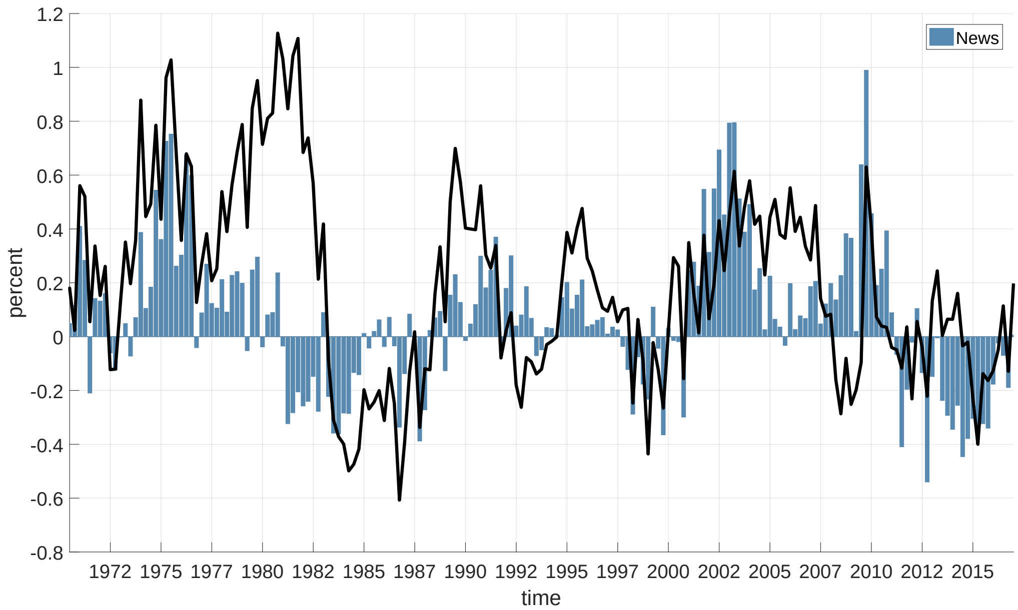
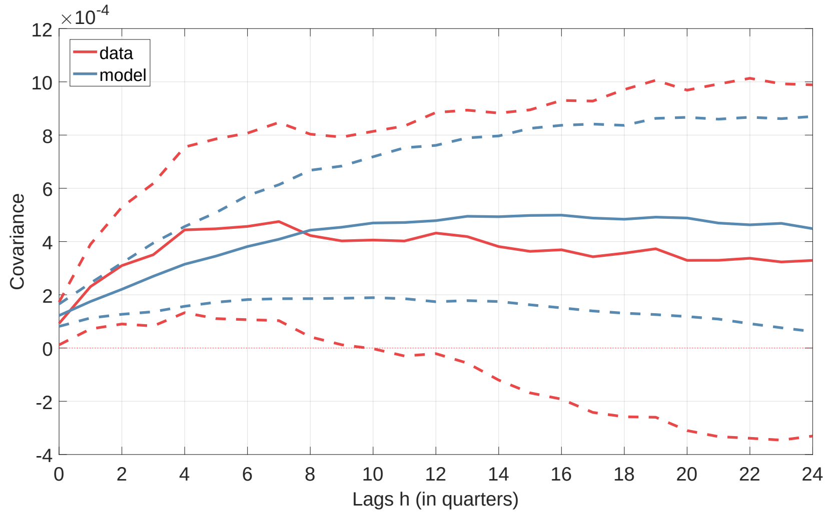
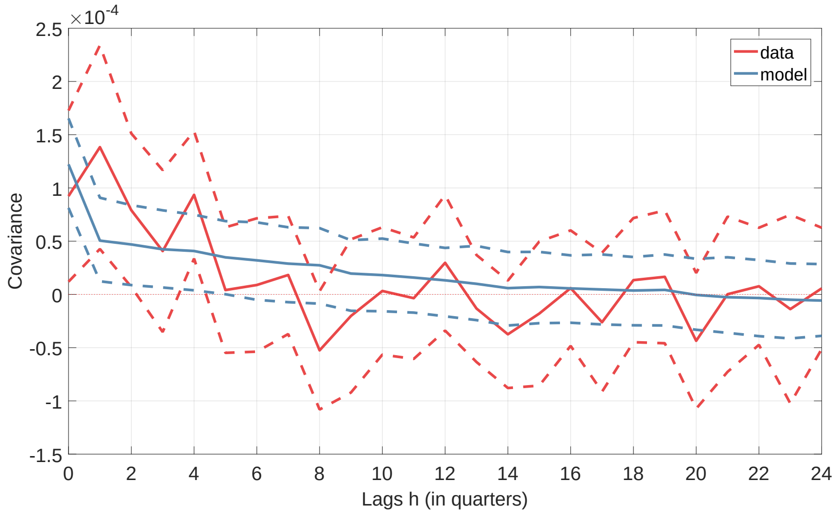



FIGURE 4: **Natural vs. Actual Rate**: This figure shows the difference between the natural and the actual real interest rates, $r^{\star} - r$, with all shocks (black line) and with news shocks only (blue bars). The figure shows the corresponding median values across the 5'000 shock time series resulting from the particle filter.

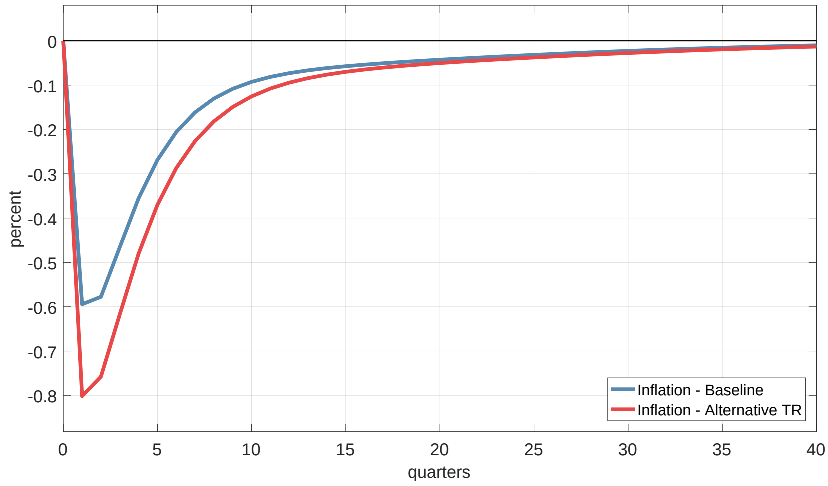



(a) Covariance of log $c_{t+1+h}/c_t$ and log $R_{t,t+1}$.

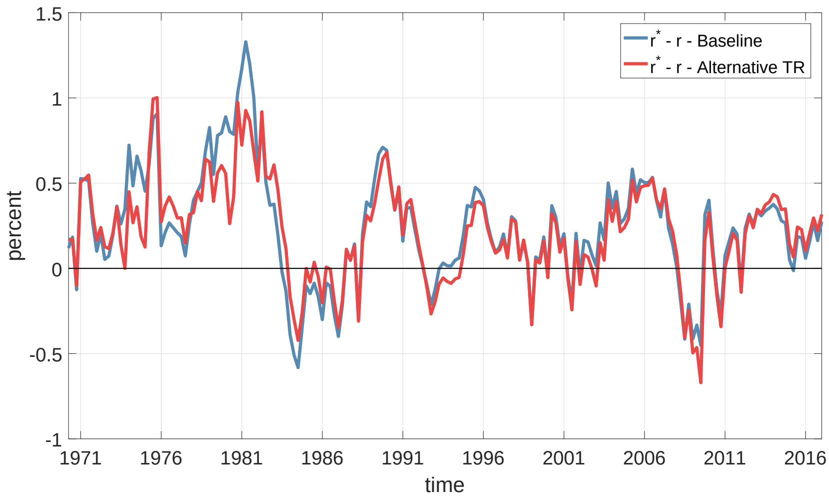



(b) Covariance of log $c_{t+1+h}/c_{t+h}$ and log $R_{t,t+1}$.

FIGURE 5: **Predictability of Consumption Growth**: Panel A plots the covariance of log $c_{t+1+h}/c_t$ and log $R_{t,t+1}$ both in the data and the model. Panel A plots the covariance of log $c_{t+1+h}/c_{t+h}$ and log $R_{t,t+1}$ The empirical sample consists out of quarterly data from 1970:1 to 2016:2. Corresponding model data is obtained from simulating the model 100 times for 185 quarters. While 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.

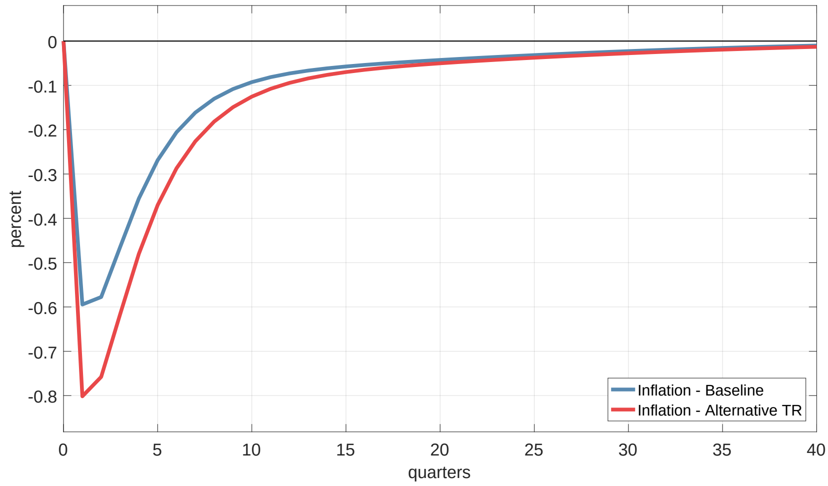



(a) IRF Inflation.

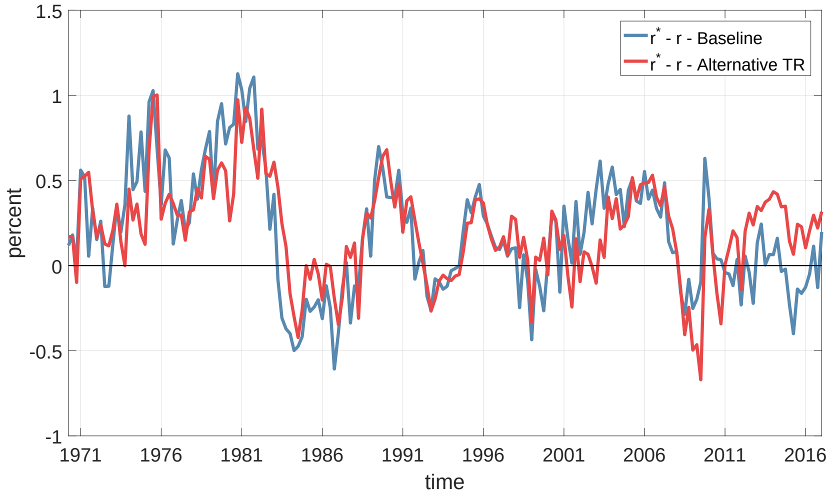



(b) Natural vs. Actual Rate.

Figure 6: **Alternative Taylor Rule**: Panel A plots the impulse responses of inflation to a 1-quarter news shock in the baseline model and a model with a forward-looking Taylor rule. Panel B reports the difference between the natural and the actual real interest rates, $r^{\star} - r$, in the baseline model and a model with a forward-looking Taylor rule as specified in equation ... In both models, news are restricted to 1-quarter news shocks. The correlation between the two lines in Panel B is 0.93.




(a) IRF Inflation.




(b) Natural vs. Actual Rate.

FIGURE 7: **Alternative Taylor Rule**: Panel A plots the impulse responses of inflation to a 1-quarter news shock in the baseline model and a model with a forward-looking Taylor rule. Panel B reports the difference between the natural and the actual real interest rates, $r^{\star} - r$, in the baseline model and a model with a forward-looking Taylor rule as specified in equation ... The correlation between the two lines in Panel B is 0.77.

# A Appendix

## A.1 Equilibrium conditions

Together with the exogenously given (1), (7), (8), (13)-(15), equilibrium is characterised by the following conditions:

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

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

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

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

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

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

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

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

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

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

$$Y_t = C_t + I_t,$$

where

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

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

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

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

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

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

Following Barsky and Sims (2011), the news shock is identified as the innovation that accounts for the maximum forecast error variance share (MFEV) of productivity over a given forecast horizon, but with the additional restriction that the innovation is orthogonal to current productivity. This is a partial identification approach that does not require us taking a stand on the nature of non-news shocks. We rely on a partial identification since full identification approaches like Beaudry and Portier (2006) and Beaudry and Lucke (2010) are potentially subject to robustness issues (see Kurmann and Mertens (2014) and Fisher (2010) a discussion). Specifically, we follow Kurmann and Otrok (2017) and include forecast horizons between 0 and 80 quarters in the MFEV objective. Since the forecast error variance is a squared object, an additional rotation condition is needed to sign the shock. As discussed in Kurmann and Otrok (2017) one needs to be careful with imposing the rotation condition at too short of a horizon if the response of productivity to a news shock is delayed as is argued for example by Beaudry and Portier (2006) or if the response is surrounded by substantial uncertainty. See also Cascaldi-Garcia (2017).

We therefore impose the rotation condition at 40 quarters, although none of the results would change if we imposed the rotation condition at 20 quarters.

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

Figure A.2 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 A.2 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.3 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.3 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.3 in turn compares the results for different numbers and identities of observables. Again, the results are largely robust to changing the set of observables. As before, the correlations coefficients of the baseline specification with 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 described by:

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

where $f_t$ is the risk factor. When there is spread in the expected returns across portfolios, there should also be statistically significant spread in the betas across portfolios. With this in mind, we test whether for each factor (consumption or SDF) filtered from our news model, the factor betas are jointly significantly different from zero. We compute standard errors using standard system OLS formulas, as well as GMM-based procedures. Using any of these procedures, Table A.1 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 $j = SDF, C$ filtered from our news model.

Table A.1: **SDF and Consumption Betas: Tests for Spread and against Zero**

This table reports $p$-values for tests of the hypotheses that $\beta_{ij} = \beta_j, \forall i$ (Panel A) and $\beta_{ij} = 0, \forall i$ for each factor $j = SDF, C$ (Panel B).

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

## A.7 Horse race 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 celebrated Parker and Julliard (2005) ultimate consumption growth. To this end we run cross-sectional regressions with simple regression betas (equivalently, asset covariances with the factors) as the explanatory variables. Hence Table 9 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

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

We follow Parker and Julliard (2005) and pick $S = 11$ quarters.

Panel A 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 5 – 7). We confirm the original results in Parker and Julliard (2005): a slow moving three-year consumption growth perform better compared with the raw one-quarter consumption growth in Table 5 – Panel B. The main difference is that there is substantial uncertainty in the risk price estimates.

Panel B 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.

Panel C shows the results of a multi-factor model that includes the SDF filtered from our news model along with the ultimate consumption growth. Compared with Panel B we observe substantial uncertainty around both risk prices estimates, the one on news-based SDF and that of ultimate consumption. Similar to Panel B, we observe that accounting for news increases the cross-sectional $R^2$, and reduces 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 Figures

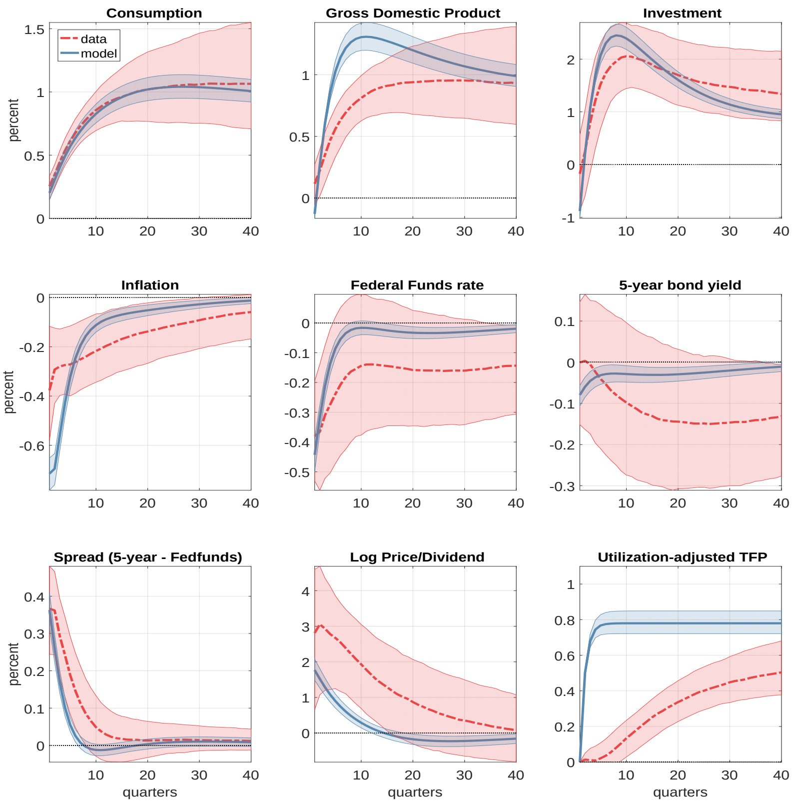



FIGURE A.1: **Impulse response function to a 1-quarter news shocks**: This figure plots the impulse response functions of consumption, output, investment, inflation, the Federal Funds rate, 5-year bond yield, the slope of the yield curve, the log price-dividend ratio and total factor productivity to a 1-quarter news shock both in the data (red dashed line) and the baseline model (blue solid line). The red and blue shaded areas correspond to 95% confidence bands in the data and the model, respectively. The theoretical responses correspond to 1.2 standard deviation 1-quarter news shock. 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).

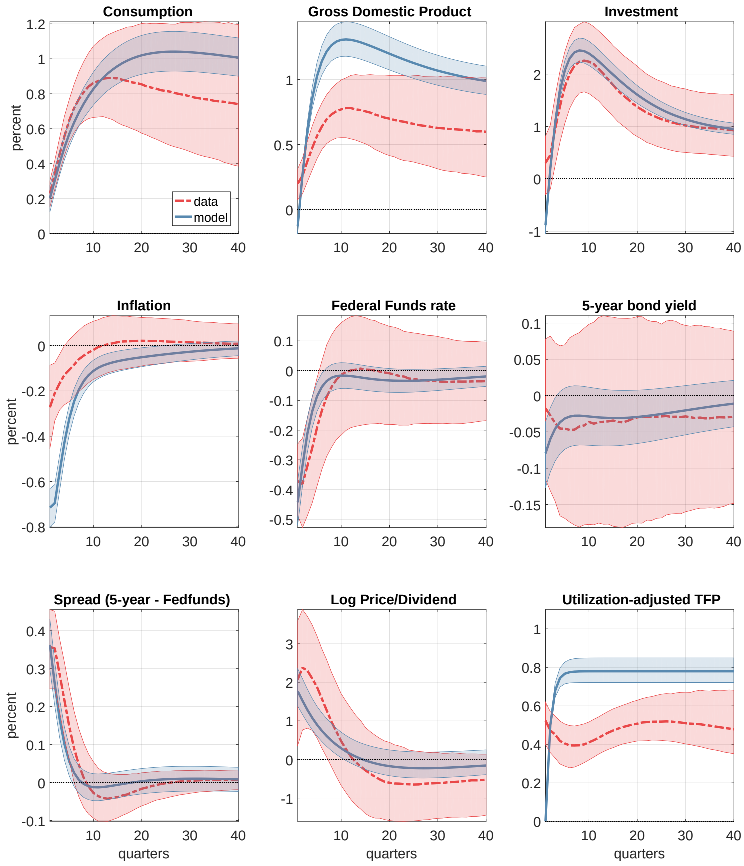
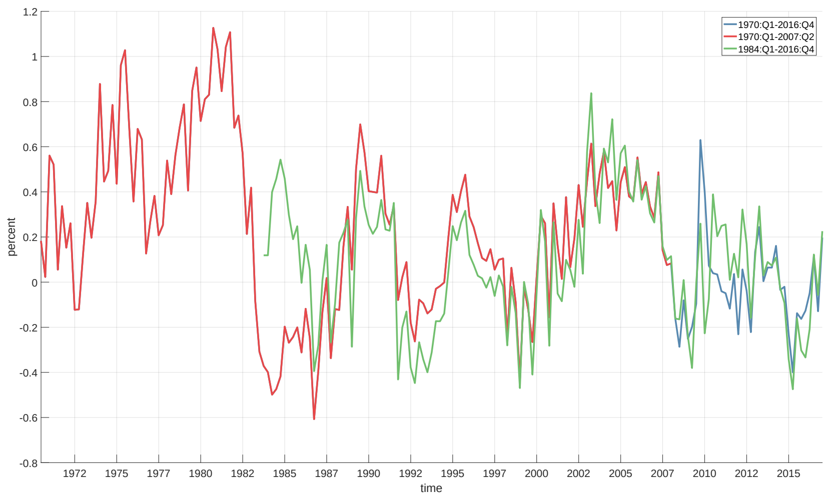
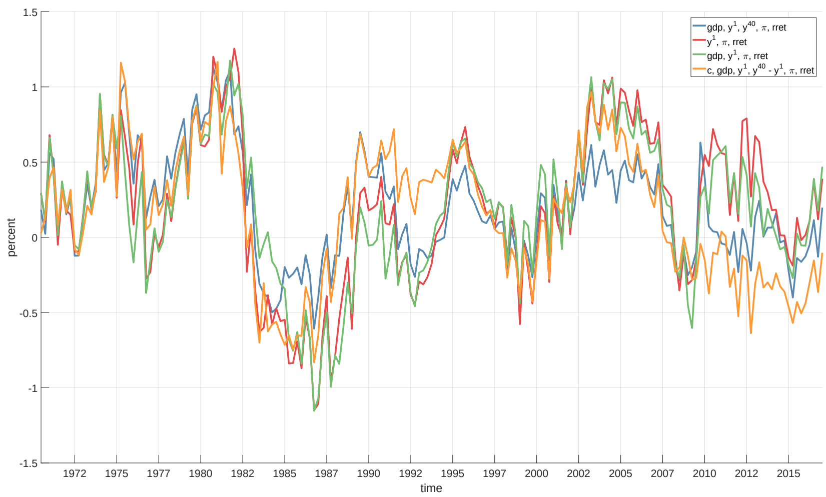



FIGURE A.2: **Impulse Responses to News Shocks - Kurmann and Sims (2017) Identification**: This figure plots the impulse response functions of consumption, output, investment, inflation, the Federal Funds rate, 5-year Treasury yield, the slope of the yield curve, the log price-dividend ratio and total 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 $\sigma^2_{XQ}/(\sigma^2_{1Q} + \sigma^2_{4Q} + \sigma^2_{8Q})$ 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.




(a) Different Sample Periods.




(b) Different Observables.

Figure A.3: **Robustness of Shock Filtering**: This figure plots the resulting difference between the natural and the real interest rate, $r^\star - r$ when we vary the sample period (Panel a) or the number and identity of observables (Panel b) when filtering the structural shocks. The graphs show the corresponding median values across the 5'000 shock time series resulting from the particle filter.

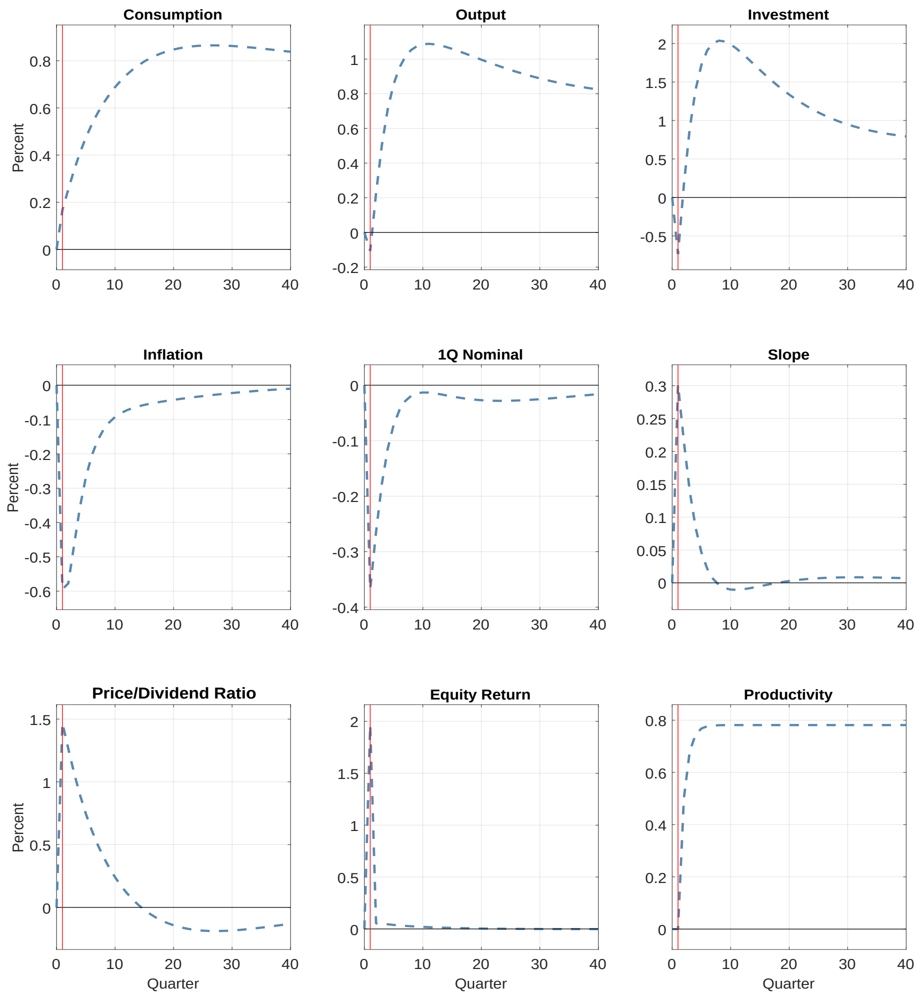



FIGURE A.4: **Impulse response function to a 1-quarter news shock**: This figure plots the theoretical impulse response functions of consumption, output, investment, inflation, the Federal Funds rate, 5-year bond yield, the slope of the yield curve, the log price-dividend ratio and total factor productivity to a one standard deviation 1-quarter news shock in the baseline model (blue dashed line). The red vertical line marks the quarter when the shock hits the system.

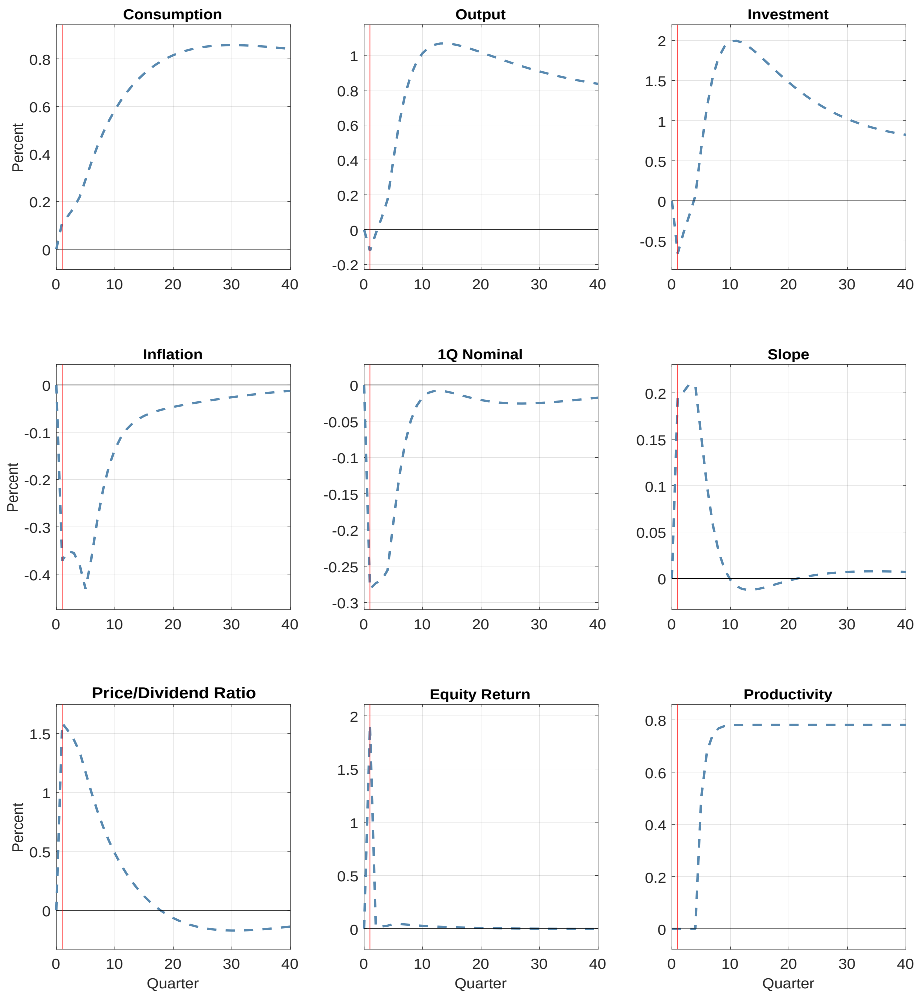



FIGURE A.5: **Impulse response function to a 4-quarter news shock**: This figure plots the theoretical impulse response functions of consumption, output, investment, inflation, the Federal Funds rate, 5-year bond yield, the slope of the yield curve, the log price-dividend ratio and total factor productivity to a one standard deviation 4-quarter news shock in the baseline model (blue dashed line). The red vertical line marks the quarter when the shock hits the system.

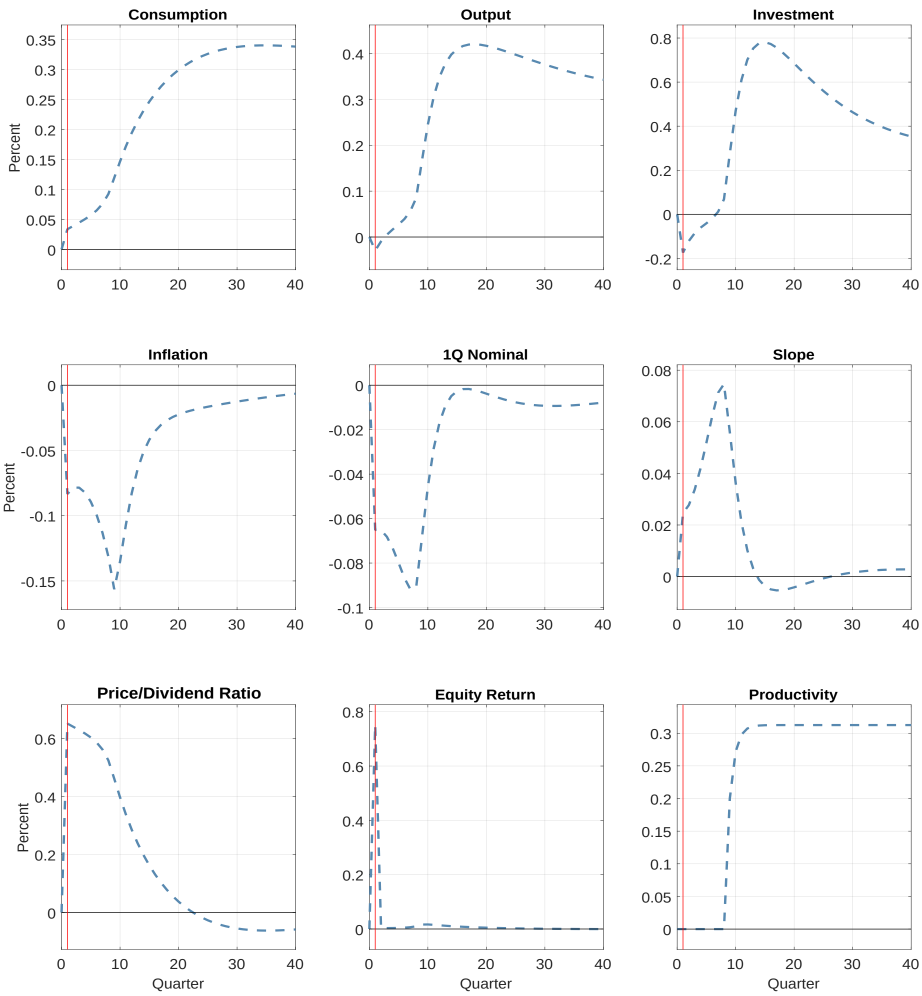



Figure A.6: **Impulse response function to a 8-quarter news shock**: This figure plots the theoretical impulse response functions of consumption, output, investment, inflation, the Federal Funds rate, 5-year bond yield, the slope of the yield curve, the log price-dividend ratio and total factor productivity to a one standard deviation 8-quarter news shock in the baseline model (blue dashed line). The red vertical line marks the quarter when the shock hits the system.