Why Does the Fed Move Markets so Much?
A Model of Monetary Policy and Time-Varying Risk Aversion

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Abstract

We show that endogenous variation in risk aversion over the business cycle can jointly explain financial market responses to high-frequency monetary policy shocks with standard asset pricing moments. We newly integrate a work-horse New Keynesian model with countercyclical risk aversion via habit formation preferences. In the model, a surprise increase in the policy rate lowers consumption relative to habit, raising risk aversion. Endogenously time-varying risk aversion in the model is crucial to explain the large fall in the stock market, the cross-section of industry returns, and the increase in long-term bond yields in response to a surprise policy rate increase.

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1 Introduction

Why do stock markets fall so much in response to a surprise hike in the monetary policy rate? Does the stock market provide high-frequency evidence that monetary policy stimulates the real economy? Or, conversely, does monetary policy drive the stock market by calming or exciting investors' nerves, divorced from its real effects? We show that the classic idea that investors are less able to bear risk after bad economic shocks can reconcile many empirical findings from the growing literature on high-frequency monetary policy shocks with standard asset pricing facts, such as the high volatility and predictability of stock returns (Shiller (1981)). The intuition is that a surprise hike in the monetary policy rate lowers consumption and output, which causes risk aversion to rise, and explains the large empirical drop in the aggregate stock market and the large increase in bond yields (Bernanke and Kuttner (2005), Hanson and Stein (2015), Nakamura and Steinsson (2018)).

Figure 1 updates the classic finding of Bernanke and Kuttner (2005) that a surprise increase in the short-term federal funds rate around FOMC announcements is typically accompanied by a significant decrease in stock prices.[1] However, the interpretation of this finding is not so simple, as the peak response of output is typically delayed, short-lived, and significantly smaller than the stock response (see e.g. Christiano, Eichenbaum, and Evans (1999) and Ramey (2016) for reviews). Further, in a Campbell and Ammer (1993) decomposition Bernanke and Kuttner (2005) attribute the majority of the empirical stock market response to changes in risk premia. We reconcile these seemingly contradictory findings with a single mechanism, namely risk aversion varying endogenously with economic conditions, disciplined by standard asset pricing moments.

Our key deviation from the standard New Keynesian model is that we assume that agents' utility depends on consumption relative to a slowly-moving habit or subsistence level, so risk aversion increases when consumption falls close to habit. While habits in finance models have been used to model variation in risk premia and in particular the high volatility and predictability of stock returns (Campbell and Cochrane (1999)), purely macroeconomic models have used consumption habits to explain hump-shaped consumption and output responses to monetary policy shocks (Fuhrer (2000), Christiano, Eichenbaum, and Evans (2005)). We use the habit formulation of Campbell, Pflueger, and Viceira (2020), which unites both purposes.

We model monetary policy through a classic Taylor (1993)-type rule for the short-

[1]Figure 1 uses 30 minute federal funds rate surprises implied by the current month future and 30 minute changes in the value-weighted stock market return that we compute from from Trade and Quote (TAQ) data. The sample period is all scheduled FOMC announcements from February 1994 through March 2019. For a detailed data description see Section 4.

term interest rate. To keep the model as disciplined and off-the-shelf as possible, the only shock is a shock to the monetary policy rate. The shock is assumed to be conditionally homoskedastic, so time varying risk premia arise endogenously from preferences rather than from auxiliary assumptions about time-varying quantities of risk. We close the macroeconomic side of the model by assuming infrequent price-setting in the manner of Calvo (1983). For simplicity we focus on the polar case with perfectly sticky prices, consistent with recent estimates of a flat Phillips curve (e.g. Nakamura and Steinsson (2018)), though we consider a nonzero Phillips curve slope in an extension.

Stocks in the model represent a levered claim to aggregate consumption, while preserving the cointegration of consumption and dividends. Individual industry portfolios are modeled by assuming that their cash flow cyclicality matches their unconditional low-frequency stock market beta in the data. High-frequency asset price changes around FOMC dates are modeled as changes around a small monetary policy shock. The model is conveniently solved in two steps. We first solve for exactly log-linear macroeconomic dynamics from consumers' intertemporal Euler equation, firms' profit optimization, and the log-linear monetary policy rule. We then solve numerically for asset prices to preserve their full nonlinearity, following the best practices of Wachter (2005).[2]

We calibrate the model to match standard macro-asset pricing moments, and choose standard parameter values from the literature as much as possible. For a small number of parameters we explicitly target moments in the data. The Campbell, Pflueger, and Viceira (2020) lag parameters in consumption habits are used to fit the lagged output response to monetary policy shocks in the data. The volatility of the quarterly monetary policy shock, which is the only shock in our parsimonious model, matches the volatility of annual consumption growth. Only one parameter - the portion of monetary policy shocks around monetary policy announcements – is set to match a high-frequency moment, namely the volatility of federal funds rate shocks in 30 minute windows around FOMC announcements. However, varying this parameter within a plausible range has very little impact on the results.

The calibrated model matches standard asset pricing moments on quarterly stock and bond returns. Despite the somewhat more complicated habit dynamics needed to fit macroeconomic dynamics, the model accounts for the empirical equity premium, high stock volatility, stock return predictability and persistent price-dividend ratio similarly to Campbell and Cochrane (1999). Said differently, the additional habit terms used to integrate finance habits with the New Keynesian Euler equation block do not hurt the

[2]By solving for log-linear macroeconomic dynamics, we keep the asset pricing solution tractable and comparable to a long-standing literature. As the consumption Euler equation and monetary policy rule are already exactly log-linear, and we preserve the full nonlinearity of asset prices, our numerical solution is close to exact for the polar case with fully sticky prices.

model's ability to match quarterly stock market moments. The model also matches the upward-sloping term structure, and generates a high quarterly bond return volatility for 10-year Treasury bonds. However, it falls short of matching the predictability of bond returns in the data. The reason is simply that the real risk-free rate in our model follows a Taylor (1993)-type log-linear monetary policy rule, which is not that highly correlated with time-varying risk aversion in the stock market.

Despite not explicitly targeted in the calibration, the model naturally explains a wide range of asset pricing facts around high-frequency monetary policy shocks. The model reconciles the large stock market response to a surprise federal funds rate increase, depicted in Figure 1, with a moderate and delayed textbook response for consumption and output. Even though the interest rate and output gap responses in the model largely dissipate within 10 quarters after the shock, long-term asset prices respond strongly due to time-varying risk premia. As is standard in New Keynesian models, a higher policy rate leads consumers to increase savings and reduce consumption. In our model, this macroeconomic effect endogenously raises risk aversion as consumption declines towards slowly-moving habit. The stock market therefore falls for two reasons. First, because the risk-neutral discounted value of future dividends declines. Second, investors have lower willingness to pay for risky stocks, driving down stock market valuations further. The risk premium effect in the model is quantitatively important and represents 80% of the overall stock market response, in line with Bernanke and Kuttner (2005)'s decomposition of the empirical stock market response.

While the interest rate and output gap responses in the model are short lived, the implied risk premium responses are much more persistent. We thereby contribute to understanding the puzzle of how short-lived monetary policy shocks can lead to large and persistent changes in long-lived assets (Bianchi, Lettau, and Ludvigson (2020)). The solution that we propose is that while the monetary policy shock is short lived, it triggers a change in risk aversion that is much more persistent as habit adjusts slowly to the change in consumption. The persistence of surplus consumption (and hence risk aversion) in our model is not a free parameter, but instead is calibrated to the same value as in Campbell and Cochrane (1999) to match the persistence of the equity price-dividend ratio in quarterly data. We thereby show that the same dynamics that explain standard properties of quarterly stock returns also explain high-frequency asset price responses to monetary policy shocks.

Our model of endogenously time-varying risk aversion not only matches the average stock market response to fed funds surprises in the data, but also two important state-contingent features of this response. First, the model matches the fact that the empirical stock market response to a fed funds surprise is larger when investor risk aversion is high, as captured by the VIX in the data. This is a natural prediction of our model where risk aversion is high and volatile when consumption is close to habit. Second, the model matches the empirical finding that small positive vs. negative federal funds rate surprises have symmetric effects on stock prices. The model reconciles these two empirical findings because risk aversion is globally convex but nonetheless locally kink-free.

We then show that the mechanism of endogenously time-varying risk aversion can also explain the practically relevant cross-section of industry stock returns around monetary policy announcements. We focus on the best-known cross-sectional result around monetary policy announcements and update Bernanke and Kuttner (2005)'s empirical findings on Fama-French 10 industry returns using intraday data. We confirm that the relative magnitude of industry responses to high-frequency fed funds surprises increases one-for-one with industry cyclicality, as measured by unconditional quarterly industry stock return betas. Further, the empirical state-contingency of stock return responses across high- and low-VIX states is also particularly pronounced for high-beta industries, as one would expect if risk aversion responds to monetary policy shocks. The model easily replicates these empirical findings, because an endogenous increase in risk aversion raises risk premia proportionately to each industry's payoff comovement with consumption. Our model therefore fits with a broader empirical literature that has found that the conditional CAPM holds on FOMC announcement dates across a variety of stock portfolios and across asset classes (e.g. Savor and Wilson (2014)).[3]

The ability of our model to explain asset price responses around monetary policy shocks also extends to long-term bond yields. An active and growing literature documents that the empirical response of real long-term Treasury yields to monetary policy shocks is large. The magnitude of this effect is surprising when viewed from traditional New Keynesian models with constant risk aversion (Hanson and Stein (2015), Nakamura and Steinsson (2018)). The model replicates the central findings in this empirical literature, namely that long-term real and nominal bond yields respond strongly to high-frequency monetary policy shocks around monetary policy announcements. Given that our model does not feature forward guidance shocks, it also does remarkably well at matching the particularly large empirical long-term bond yield responses to Nakamura and Steinsson (2018) monetary policy shocks, though a gap between the model and the

[3]The empirical literature on asset prices around FOMC dates has emphasized broadly two different sets of facts. The first type, and the one we study in this paper, has estimated regression coefficients of asset prices onto monetary policy surprises during narrow windows around announcements on the FOMC date. A second prominent strain has documented that the average level of equity returns is typically higher prior to FOMC dates (Lucca and Moench (2015), Cieslak, Morse, and Vissing-Jorgensen (2019), Cieslak and Pang (2021)). We do not study the pre-FOMC announcement drift in this paper, though we believe it would be fruitful to build on our framework to understand how time-varying risk premia amplify fundamental news during the pre-FOMC period.

data remains. Decomposing model long-term Treasury yields into risk-neutral and risk premium components shows that risk premia account for roughly half of the model Treasury yield responses. This means that the traditional channel of changing expectations of future interest rates, that is present in most standard New Keynesian models, accounts for about half of the empirical response. The other half is accounted for by the new channel, namely the endogenous change in risk aversion following a monetary policy shock.

We contribute to the literature by explaining stock and bond responses to monetary policy shocks with the classic idea that risk-bearing capacity varies over the business cycle. This is a general point independent of the specific microfoundations of time-varying risk aversion. While our model builds on habit formation preferences, our results on the magnitude and persistence of asset price responses to monetary policy shocks should be regarded more broadly as the result of countercyclical risk premia, whether they are generated from the price of risk or quantity of risk as in Jurado, Ludvigson, and Ng (2015). The advantage of our habits model is that it is relatively simple and its implications for standard asset pricing moments are well-understood, allowing us to unify a wider range of empirical asset pricing facts with one single mechanism. Our focus on preferences is also useful because it shows that one does not have to assume that monetary policy shocks have a large effect on the quantity of risk, which would likely be hard to pin down in high-frequency data. We therefore view our contribution as complementary to recent innovations in understanding the role of heterogeneous agents for monetary policy (Kaplan, Moll, and Violante (2018), McKay, Nakamura, and Steinsson (2016), Auclert, Rognlie, and Straub (2020)) and as microfoundations for time-varying risk aversion (Chan and Kogan (2002), Drechsler, Savov, and Schnabl (2018), Kekre and Lenel (2020)).[4]

We also add to a growing literature modeling stocks and bonds within endogenous macroeconomic dynamics. Bianchi, Lettau, and Ludvigson (2020) argue within a New Keynesian model with learning that changes in monetary policy regimes can explain the secular movements in the real risk-free rate. Prior work has used ambiguity aversion (Bianchi, Ilut, and Schneider (2018)), disaster risks (Gourio (2012), Kilic and Wachter (2018)) and long-run risks (e.g. Kung (2015), Gourio and Ngo (2020)) to understand asset pricing implications within models of the macroeconomy. A portion of this literature, such as Rudebusch and Swanson (2012), has focused on bond term premia within DSGE models. Other papers have studied stocks and bonds (e.g. Swanson (2019)), but not asset price responses around high-frequency monetary policy shocks.

Across these different modeling approaches, a model of endogenously time-varying risk aversion is uniquely suited to explain empirical facts around monetary policy announce-

[4] Similarly, we view our model as complementary to the liquidity-based model of stock responses to federal funds rate innovations of Lagos and Zhang (2020).

ments, because it naturally generates large swings in risk premia from from small level changes in interest rates. Some previous research, including Uhlig (2007), Dew-Becker (2014), Rudebusch and Swanson (2008), Lopez (2014), Stavrakeva and Tang (2019), Challe and Giannitsarou (2014), and Bretscher, Hsu, and Tamoni (2019) has embedded simplified finance habit preferences into a New Keynesian model. Our model differs from these other papers in that we preserve the full nonlinearity of preferences that Campbell and Cochrane (1999) find crucial to explain high stock return volatility with a smooth risk-free rate. We use Campbell, Pflueger, and Viceira (2020)'s preferences to unify a model of time-varying risk aversion with a standard New Keynesian model.[5]

The paper is organized as follows. Section 2 presents the model and the solution method. Section 3 discusses the calibration and shows that the model fits quarterly asset prices. Section 4 compares asset price responses to high-frequency monetary policy shocks in the model and in the data. Section 5 concludes.

2 Model

This Section describes the model setup for habit preferences and the macroeconomy. The model is as simple as possible while capturing our main empirical objects of interest: the macroeconomic and asset price response to a monetary policy shock. To keep the model disciplined there is only a single conditionally homoskedastic source of uncertainty, namely an i.i.d. monetary policy shock to a Taylor (1993)-type monetary policy rule. We use lower-case letters for logs throughout.

2.1 Habit preferences

A representative agent derives utility from real consumption C_t relative to a slowly-moving habit level H_t

$$U_t = \frac{(C_t - H_t)^{1-\gamma} - 1}{1-\gamma} \tag{1}$$

Habits are external, meaning that they are shaped by aggregate consumption and households do not internalize how habits might respond to their personal consumption choices. The parameter γ is a curvature parameter.

In this model, relative risk aversion equals $-U_{CC}C/U_C = \gamma/S_t$, where surplus consumption is the share of market consumption available to generate utility:

$$S_t = \frac{C_t - H_t}{C_t}. \tag{2}$$

[5]Different from Campbell, Pflueger, and Viceira (2020), we study the effects of monetary policy shocks.

The stochastic discount factor (SDF) M_{t+1} used to price all financial assets and to derive the macroeconomic consumption Euler equation equals:

$$M_{t+1} = \beta \frac{\frac{\partial U_{t+1}}{\partial C}}{\frac{\partial U_t}{\partial C}} = \beta \exp\left(-\gamma(\Delta s_{t+1} + \Delta c_{t+1})\right). \tag{3}$$

As equation (2) makes clear, a model for market habit implies a model for surplus consumption and vice versa. Following Campbell, Pflueger, and Viceira (2020), we model market habit implicitly by assuming that log surplus consumption, s_t, satisfies:

$$s_{t+1} = (1-\theta_0)\bar{s} + \theta_0 s_t + \theta_1 x_t + \theta_2 x_{t-1} + \varepsilon_{c,t}, \tag{4}$$

$$\varepsilon_{c,t+1} = c_{t+1} - \mathrm{E}_t c_{t+1}. \tag{5}$$

The sensitivity function $\lambda(s_t)$ takes the form:

$$\lambda(s_t) = \begin{cases} \frac{1}{\bar{S}}\sqrt{1-2(s_t-\bar{s})} - 1 & s_t \leq s_{max} \\ 0 & s_t > s_{max} \end{cases}, \tag{6}$$

$$\bar{S} = \sigma_c \sqrt{\frac{\gamma}{1-\theta_0}}, \tag{7}$$

$$\bar{s} = \log(\bar{S}), \tag{8}$$

$$s_{max} = \bar{s} + 0.5(1-\bar{S}^2). \tag{9}$$

Here, σ_c denotes the standard deviation of the consumption surprise $\varepsilon_{c,t+1}$ and $\bar{s}$ is the steady-state value for log surplus consumption. The consumption surprise is an equilibrium object depending on fundamental shocks, and we will verify in our solution that it is conditionally homoskedastic and lognormal.

The terms $\theta_1 x_t$ and $\theta_2 x_{t-1}$ are new relative to Campbell and Cochrane (1999). Here, x_t equals stochastically detrended consumption (up to a constant):

$$x_t = c_t - (1-\phi)\sum_{j=0}^{\infty} \phi^j c_{t-1-j}, \tag{10}$$

where ϕ is a smoothing parameter. For the microfoundations presented in the appendix, x_t also equals the log output gap, or the difference between between log output and log potential output under flexible prices. The specification for log surplus consumption (4) implies that log market habit follows approximately a weighted average of past log consumption. For details, see Appendix A.1.

2.2 Macroeconomic dynamics

Macroeconomic dynamics in our model are described by the simplest small-scale New Keynesian model, consisting of an Euler equation, a Phillips curve, and a monetary policy rule.

2.2.1 Euler equation

The derivation starts from the asset pricing first-order condition for the real risk-free rate r_t:

$$1 = \mathrm{E}_t \left[M_{t+1} exp(r_t) \right]. \tag{11}$$

Substituting for the SDF and surplus consumption dynamics gives (up to a constant):

$$\begin{aligned} r_t &= \gamma \mathrm{E}_t \Delta c_{t+1} + \gamma \mathrm{E}_t \Delta s_{t+1} - \frac{\gamma^2}{2} \left(1 + \lambda(s_t)\right)^2 \sigma_c^2, & (12) \\ &= \gamma \mathrm{E}_t \Delta c_{t+1} + \gamma \theta_1 x_{t-1} + \gamma \theta_2 x_{t-2} + \underbrace{\gamma(\theta_0 - 1)s_t - \frac{\gamma^2}{2} \left(1 + \lambda(s_t)\right)^2 \sigma_c^2}_{=0}. & (13) \end{aligned}$$

For the assumed sensitivity function the last two terms drop out. Using equation (10) and rearranging gives the *exactly* loglinear **Euler equation:**

$$x_t = f^x x_{t+1} + \rho^x x_{t-1} - \psi r_t, \tag{14}$$

where

$$\rho^x = \frac{\theta_2}{\phi - \theta_1}, f^x = \frac{1}{\phi - \theta_1}, \psi = \frac{1}{\gamma(\phi - \theta_1)}. \tag{15}$$

Because the Euler equation is endogenous to preferences this New Keynesian block does not introduce any new free parameters. Further, we impose the restriction common for New Keynesian models that the forward- and backward-looking terms in the Euler equation add up to one ($\rho^x = 1 - f^x$), pinning down θ_2 in terms of θ_1 and ϕ

$$\theta_2 = \phi - 1 - \theta_1. \tag{16}$$

The link between preferences and the New Keynesian block in equations (15) and (16) makes clear that non-zero values for the Campbell, Pflueger, and Viceira (2020) habit parameters, θ_1 and θ_2, are needed to generate a New Keynesian block with forward- and backward-looking coefficients. If instead θ_1 and θ_2 were zero, as in Campbell and Cochrane (1999), the backward-looking term in the consumption Euler equation would be inconsistent with the stochastic discount factor. The macroeconomics literature has found that backward-looking terms in the Euler equation are necessary to generate empirically-plausible lags for consumption and output responses to monetary policy shocks (Fuhrer (2000), Christiano, Eichenbaum, and Evans (2005)).

2.2.2 Phillips curve

The supply side of the model can be summarized by the log-linearized **Phillips curve:**

$$\pi_t \quad = \quad f^{\pi} E_t \pi_{t+1} + \rho^{\pi} \pi_{t-1} + \kappa x_t, \tag{17}$$

for constants ρ^{π}, f^{π} and κ.

We provide detailed microfoundations in the Appendix, and only briefly summarize them here. The Phillips curve describing the inflation dynamics arises from log-linearizing the profit first-order condition of firms that face infrequent opportunities to reset product prices in the manner of Calvo (1983), and whose prices are indexed to past inflation otherwise. The parameter κ is a price-flexibility parameter. In order to present the simplest possible model of monetary policy and finance habits we do not explicitly model real investment and the aggregate resource boils down to consumption equals output

$$C_t = Y_t. \tag{18}$$

To keep the number of free parameters to a minimum, our baseline calibration follows Caballero and Simsek (2020) in considering the special case with fully sticky prices, i.e. $\kappa = 0$. This implies that inflation is constant and the parameters ρ^{π} and f^{π} drop out.

2.2.3 Monetary policy rule

Let i_t denote the log nominal risk-free rate available from time t to $t+1$. Monetary policy is described by the following rule (ignoring constants):

$$i_t \quad = \quad \rho^i i_{t-1} + \left(1 - \rho^i\right) \left(\gamma^x x_t + \gamma^{\pi} \pi_t\right) + v_t., \tag{19}$$

$$v_t \quad \sim \quad N\left(0, \sigma^2_{MP}\right) \tag{20}$$

Here, $\gamma^x x_t + \gamma^{\pi} \pi_t$ denotes the central bank's interest rate target, to which it adjusts slowly with a lag coefficient ρ^i. The monetary policy shock, v_t, is assumed to be mean-zero, serially uncorrelated and conditionally homoskedastic. A positive monetary policy shock represents a surprise tightening of the short-term nominal interest rate above and beyond what would be predicted by the rule. The policy rate then mean-reverts slowly at rate ρ^i. In our baseline case with fully sticky prices, the monetary policy inflation weight

γ^π drops out. To keep the solution for macroeconomic dynamics log-linear we use the common log-linear approximation for the real risk-free rate $r_t = i_t - E_t\pi_{t+1}$.[6]

2.3 Stocks and bonds

We model stocks as a levered claim on consumption, as in Abel (1990) and Campbell (2003). Stocks therefore represent a generic procyclical asset class. Let P_t^c denote the price of a claim to the entire future consumption stream C_{t+1}, C_{t+2},... At time t the aggregate firm buys P_t^c and sells equity worth δP_t^c, with the remainder of the firm's position financed by one-period risk-free debt worth $(1-\delta)P_t^c$. Zero-coupon bonds represent claims to one dollar n periods in the future. To model stock portfolios of cyclical vs. less cyclical industries we assume that industry j represents a consumption claim similar to the aggregate stock market with $\delta^j \neq \delta$. Industry portfolios are assumed to aggregate up to the market portfolio, so the equilibrium is unaffected.

2.4 High-frequency FOMC announcement returns

To model high-frequency monetary policy surprises within a quarterly model we make the simplifying assumption that FOMC news is announced instantaneously, i.e. within an infinitely short time interval. We further make the simplifying assumption that FOMC dates occur at the end of the quarter, so post-FOMC asset prices correspond to end-of-quarter asset prices.[7] In order to model the discrete arrival of news on FOMC dates, we assume that the quarterly fundamental shock vector v_t consists of independent pre-FOMC v_t^{pre} and FOMC v_T^{FOMC} components

$$v_t = v_t^{pre} + v_t^{FOMC},$$

so v_t^{FOMC} denotes the portion of the monetary policy news shock is revealed on FOMC dates. The key features of v_t^{FOMC} mapping into monetary policy surprises in the data are that it is not contaminated by other macroeconomic news and that it is typically much smaller than v_t^{pre}. Pre-FOMC asset prices in our model differ from quarter $t-1$ asset prices because they also reflect information encoded in v_t^{pre}, such as the endogenous output gap response to changes in the policy rate. We compute quarter t pre-FOMC asset prices at the expected quarter t state vector conditional on v_t^{pre}.

[6] For our baseline calibration with perfectly sticky prices, inflation drops out and this approximation error shrinks to zero. We do not explicitly model the zero-lower-bound (ZLB) for simplicity, leaving this application for future research. One simple way to incorporate the ZLB explicitly into the model would be through a Markov regime switching model, which would preserve the tractability of the model.

[7] Given that our results are robust to varying the volatility of news released on FOMC dates (Appendix E.3), modeling FOMC dates as occurring every six weeks is unlikely to change our findings.

Model high-frequency log stock returns around monetary policy news then are simply defined as the difference between post- minus pre-FOMC log stock prices. We define high-frequency changes in any bond yield as the difference between post- minus pre-FOMC log bond yields. For details of model high-frequency asset price changes see Appendix C.8.

2.5 Solution

We solve the model in two steps. First, we solve for log-linear macroeconomic dynamics. Second, we use numerical methods to solve for highly non-linear asset prices. The tractability of this two step solution method is achieved because the surplus consumption ratio does not appear directly in the New Keynesian Euler equation or the monetary policy rule.

2.5.1 Macroeconomic equilibrium dynamics

We solve for the dynamics of the log-linear state vector

$$Y_t = [x_t, \pi_t, i_t]'. \tag{21}$$

Equilibrium macroeconomic dynamics are determined by the consumption Euler equation (14), the Phillips curve (17), and the monetary policy rule (19). We solve for a minimum state variable equilibrium of the form:

$$Y_t = BY_{t-1} + \Sigma v_t, \tag{22}$$

where B and Σ are $[3 \times 3]$ and $[3 \times 1]$ matrices, respectively. We solve for the matrix B using Uhlig (1999)'s formulation of the Blanchard and Kahn (1980) method. Having solved for the state vector Y_t, equilibrium consumption dynamics follow by inverting the relationship (10). In our calibration, there exists a unique equilibrium of the form (22) with non-explosive eigenvalues. However, as in most New Keynesian models, there may be further equilibria with additional state variables or sunspots (Cochrane (2011)), but resolving these issues is beyond this paper. Note that equation (22) implies that macroeconomic dynamics are conditionally log-normal, so combined with the output gap-consumption link (10) consumption surprises $\varepsilon_{c,t+1}$ are indeed conditionally lognormal in equilibrium.

2.5.2 Asset pricing recursions

Having solved for log-linear macroeconomic dynamics, we next use numerical methods to solve for highly nonlinear asset prices. Stock and bond prices depend on one additional state variable, namely the log surplus consumption ratio s_t, in addition to the macroeconomic state vector Y_t.

We use the following recursion to solve for the price-consumption ratio of an n-period zero-coupon consumption claim:

$$\frac{P^c_{nt}}{C_t} = \mathrm{E}_t \left[M_{t+1} \frac{C_{t+1}}{C_t} \frac{P^c_{n-1,t+1}}{C_{t+1}} \right]. \tag{23}$$

The price-consumption ratio for a claim to aggregate consumption is equal to the infinite sum of zero-coupon consumption claims:

$$\frac{P^c_t}{C_t} = \sum_{n=1}^{\infty} \frac{P^c_{nt}}{C_t}. \tag{24}$$

The price of the levered equity claim equals $P^\delta_t = \delta P^c_t$. Leverage hence scales stock returns roughly proportionally, increasing stock return volatility but leaving the Sharpe ratio unchanged. We initialize the recursions for real and nominal zero coupon bond prices:

$$P_{1,t} \quad = \quad \exp\left(-r_t\right), \; P^\$_{1,t} = \exp\left(-i_t\right). \tag{25}$$

The n-period zero coupon real and nominal prices follow the recursions:

$$P_{n,t} \quad = \quad \mathrm{E}_t \left[M_{t+1} P_{n-1,t+1} \right], \; P^\$_{n,t} = \mathrm{E}_t \left[M_{t+1} P^\$_{n-1,t+1} exp\left(-\pi_{t+1}\right) \right]. \tag{26}$$

Log real and nominal zero coupon bond yields with maturity n are defined by $y_{n,t} = -\log\left(P_{n,t}\right)/n$ and $y^\$_{n,t} = -\log\left(P^\$_{n,t}\right)/n$.

An analytic solution exists for the one-period consumption claim, the first claim in the infinite sum (24). Denoting the log return on the one-period consumption claim by $r^c_{1,t+1}$, the risk premium – adjusted for a standard Jensen's inequality term – equals the conditional covariance between the negative log SDF and and log consumption:

$$E_t \left[r^c_{1,t+1} - r_t \right] + \frac{1}{2} Var\left(r^c_{1,t+1} \right) = \mathrm{Cov}_t\left(-m_{t+1}, x_{t+1}\right) = \gamma\left(1 + \lambda\left(s_t\right)\right) \sigma^2_c. \tag{27}$$

This equation shows that the risk premium goes up as surplus consumption s_t decreases, because the sensitivity function $\lambda(s_t)$ is downward-sloping in s_t. Intuitively, risk aversion is high and volatile in states where consumption is closer to habit, driving up the risk premium investors require on a risky consumption claim.

We solve the asset pricing recursions recursively along a four-dimensional grid consisting of the macroeconomic state vector Y_t and the surplus consumption ratio s_t. Iterating along a grid, as opposed to local approximation or global solution methods, is the best practice for this type of numerical problem because it imposes the least structure (Wachter (2005)). By contrast, approximation with polynomials would miss the particularly strong non-linearity of the sensitivity function as the log surplus consumption ratio becomes small, distorting numerical asset prices even around the steady-state. Grid iteration is facilitated in our framework because macroeconomic dynamics are log-linear.

We decompose model asset prices into risk-neutral and risk premium components. Risk-neutral stock and bond prices are computed through the same recursions with the risk-neutral discount factor that is consistent with equilibrium dynamics for the real interest rate. We then compute the risk premium component of stock returns simply as the total return minus the risk-neutral return, and the risk premium component of log bond yields as the log bond yield minus the risk-neutral log bond yield. For details of the numerical solution see Appendix D.

3 Calibration and quarterly model properties

We next describe the model calibration and show that it fits standard quarterly macroeconomic and asset pricing moments, before moving on to the model's high-frequency properties in the next Section. Table 1 lists the calibration parameters and the moments targeted by each parameter. For as many parameters as possible we choose standard values that previous authors have settled on as a good match for the corresponding moment. The motivating moment in Figure 1 and other asset return moments around high-frequency monetary policy shocks are not used in the calibration and instead are left to be explained, effectively providing an external test of the model.[8]

We use a utility curvature parameter of $\gamma = 2$, which Campbell and Cochrane (1999) have found to fit the unconditional equity Sharpe in the data. The parameters for consumption growth, the real risk-free rate, and the persistence of surplus consumption are directly from Campbell and Cochrane (1999). The smoothing parameter for de-trending potential output ϕ is from Campbell, Pflueger, and Viceira (2020) who documented that $\phi = 0.93$ gives a close correlation between exponentially detrended consumption and the

[8]The only high-frequency moment used in the calibration is the standard deviation of high-frequency shocks on FOMC dates, σ_{MP}^{FOMC}. Appendix E.3 shows that all our main results are unchanged if σ_{MP}^{FOMC} is changed by an order of magnitude.

output gap from the Bureau of Economic Analysis. The monetary policy parameters take standard values from Taylor (1993) and Clarida, Gali, and Gertler (2000). Our baseline calibration sets $\kappa = 0$, so the inflation parameters ρ^π, f^π, and γ^π drop out.[9]

The following four parameters are chosen to match specific moments in the data. First, the new habit parameter θ_1 is chosen to match the hump-shape in the consumption response to a surprise monetary policy rate increase. Since the goal of this paper is reconcile the large stock response to a monetary policy shock with a moderate and delayed consumption response in line with the data, this is an important moment for our calibration. The notion that monetary policy acts with "long and variable lags" goes back at least to Milton Friedman, and has subsequently been subject to a long literature in empirical macroeconomics. We target the textbook moments of Christiano, Eichenbaum, and Evans (1999) that the trough output response occurs 4-6 quarters after the initial monetary policy shock, and measures around -70 bps for every 100 bps increase in the federal funds rate.[10] To reduce the degrees of freedom in the model, the parameter θ_2 is set so that the weights in the macroeconomic Euler equation sum to one, thereby making our macroeconomic impulse responses comparable to much of the macroceconomic literature.

To understand why we need a non-zero value for the habit parameter θ_1, Figure 2 compares the model output response to a monetary policy shock with the empirical output response from Christiano, Eichenbaum, and Evans (1999). The figure shows that the model generates a hump-shaped output response similar to the data, but only if $\theta_1 \neq 0$. By contrast, setting $\theta_1 = 0$ as in Campbell and Cochrane (1999) generates an immediate downward-spike in real output after a monetary policy shock, contrary to the empirical evidence that monetary policy acts with long and variable lags. A larger value of θ_1 in our model acts similarly to habits in the purely macroeconomic literature (see e.g. Fuhrer (2000), Christiano, Eichenbaum, and Evans (1999)), increasing the dependence of habit on the first lag of consumption. Because habit consumers' marginal utility depends on the change in consumption, a hike in interest rates leads to negative rate of change in consumption for several quarters, and a hump-shaped response in levels. For the log-linear expansion of habit see Appendix A.1.

Second, the quarterly standard deviation of the monetary policy shock σ_{MP} is set to match the unconditional volatility of consumption growth of 1.50% as in Campbell and Cochrane (1999). Our parsimonious model only has one shock, so we cannot inde-

[9] We check in Appendix E.4 that the model results for stocks are unchanged when we allow for a non-zero κ. We show bond results for different values of κ in Table 7. We check in Appendix E.2 that the particular calibrated value of the monetary policy parameter γ^x is not crucial for our main results.

[10] A range of identification approaches generate similarly hump-shaped responses to monetary policy shocks. See Ramey (2016) for a summary.

pendently match the volatility of quarterly interest rates and the volatility of quarterly consumption growth. We choose to match the volatility of quarterly consumption growth because this is the moment that determines the overall level and time-variation in risk premia. We have a separate parameter available to separate out the monetary policy shock on FOMC dates, namely σ_{MP}^{FOMC}. To have a reasonable volatility of news released around FOMC announcements, we set $\sigma_{MP}^{FOMC} = 6.52$ bps to match the volatility of fed funds surprises in 30 minute windows around FOMC announcements in our sample. Finally, we set the leverage parameter $\delta = 2/3$ to match the quarterly volatility of stock returns. Notably, the implied market leverage ratio, or the value of debt to total assets, takes a low and empirically plausible of $1 - \delta = 1/3$.

Table 2 lists parameters implied by our calibration. The discount rate, steady-state surplus consumption ratio, and maximum surplus consumption ratio are comparable to Campbell and Cochrane (1999). The forward- and backward-looking components in the macroeconomic Euler equation are in line with Fuhrer (2000) and Christiano, Eichenbaum, and Evans (2005). The small slope of the Euler equation, which is different from the Elasticity of Intertemporal Substitution in this model, is in line with the instrumental variable estimates of Yogo (2004).

3.1 Quarterly model properties

Table 3 shows that the model fits standard low-frequency moments for asset prices and the macroeconomy. The top panel shows that despite the additional structure our model does equally well on quarterly stock returns as Campbell and Cochrane (1999) and Campbell, Pflueger, and Viceira (2020). The model generates volatile stock returns with an empirically plausible equity Sharpe ratio of 0.49, an equity premium of 7.63%, and annualized equity return volatility of 15.61%. This high stock return volatility is achieved through time-varying risk premia.[11] Similarly, the model fits the persistence of the price-dividend ratio and the predictability of annual stock returns from the lagged price-dividend ratio.

The second panel summarizes bond moments in the model. The model generates an upward-sloping term structure, similarly to the data. Bond return volatility in the model is high at 3.65%, though not as high as in the data.[12] The success on the term structure

[11] To compute the empirical asset pricing moments, we use value-weighted combined NYSE/AMEX/-Nasdaq stock returns including dividends from CRSP. The dividend-price ratio is constructed using data for real S&P 500 dividends and the S&P 500 real price from Robert Shiller's website. For both bonds and stocks, we consider log returns in excess of the log T-bill rate, where the end-of-quarter three-month T-bill is from the CRSP monthly Treasury risk-free rate file. Log bond returns are derived from changes in yields in the data. End-of-quarter bond yields for both nominal Treasuries and TIPS are from the daily zero coupon curves of Gürkaynak, Sack, and Swanson (2005) and Gürkaynak, Sack, and Wright (2010). All yields and returns are continuously compounded.

[12] This is not surprising as our simple model features only one single shock and does not feature any

is achieved because bonds are risky in the model, i.e. they pay off in low marginal utility states and have a positive beta with respect to the stock market. A positive monetary policy shock increases bond yields, engineers a recession, and increases marginal utility. Because bond returns move inversely with yields, long-term bonds do badly when the marginal utility of consumption is high and require a positive risk premium. An upward-sloping term structure similar to the data results.

While the model does a good job at matching the unconditional properties of the term structure, it falls short of matching the predictability of bond returns in the data. The reason for this is simply that the real risk-free rate in our model follows a log-linear monetary policy rule and is therefore imperfectly correlated with stock market risk premia.[13]

The model's favorable quarterly asset pricing properties are achieved with reasonable macroeconomic dynamics. The volatility of annual consumption growth is very close to the targeted value of 1.50% per year. Even though not explicitly targeted, the trough response of consumption to a monetary policy shock is reasonable and similar to the empirical textbook impulse response. Our model generates a 72 bps trough decline in consumption for every 100 bps surprise in increase in the federal funds rate, very similar to the 70bps in the empirical benchmark estimation reported by Christiano, Eichenbaum, and Evans (1999). Also not explicitly targeted is the unconditional volatility of the federal funds rate. Our parsimonious model has only one shock and we therefore cannot target both the volatility of annual consumption changes and fed funds rate changes. Nonetheless, the standard deviation of annual fed funds rate changes in the model is reasonable at 2.21%, compared to 1.35% in the data over our sample. The consumption-output gap relationship also fits well. In the model, a regression of annual log consumption growth onto the annual log output gap change yields a coefficient of 0.97 (correlation 0.93) compared to a coefficient of 0.89 (correlation 0.75) in the data.

long-term inflation or growth shocks that have been argued to explain the large secular decline in 10-year nominal bond yields from around 7% at the beginning of our sample to about 2% at the end (Cieslak and Povala (2015), Bauer and Rudebusch (2020)).

[13]Our model implies a slightly negative regression coefficient of bond excess returns onto the lagged term spread because a positive monetary policy shock has opposing effects on the expectations hypothesis and risk premium components of the term spread. A positive monetary policy shock raises long-term bond risk premia but drives down the expectations hypothesis component of term spread, as the current short rate increases more than future expected short rates. Different from Wachter (2006), interest rates are log-linear in our model and bonds are consequently less risky, so the expectations hypothesis component dominates the effect on term spread. We cannot use Wachter (2006)'s preferences, because those would imply a highly nonlinear risk-free rate inconsistent with standard monetary policy rules. One possible resolution for bond return predictability could be if the quantity of risk in bonds varies over time, such as through a time-varying monetary policy rule.

3.2 Model mechanism

To better understand the model mechanism, Figure 3 shows model impulse responses to a one-standard deviation monetary policy shock for the log short-term interest rate, the log output gap, log stock excess returns, and 10-year log bond yields. Since in our baseline calibration inflation is constant, the bond yields in Figure 3 can be interpreted as either real or nominal. Quarters after the shock are shown on the x-axis. Stock returns are cumulative, i.e. a value of -7% at 8 quarters means that stock prices are 7 percent lower eight quarters after the shock than they were just before the shock. Because bond yields are inversely related to prices, an increase in the 10-year bond yield implies a decrease in the corresponding bond price.

The top-left panel in Figure 3 shows the mechanics of the shock. A positive shock leads to an increase in the short-term risk-free rate that mean-reverts with mean-reversion parameter $\rho^i = 0.8$ and converges back to zero at about ten quarters. The top-right panel illustrates the dynamics for the output gap. Like the consumption response, the output gap initially responds little. It subsequently declines and reaches a trough response of around -0.70 percentage points at 4 quarters, before converging back to its steady-state value.

Why does the output fall in response to an increase in the monetary policy rate in this model? The answer, as in most standard small-scale New Keynesian models, lies in the macroeconomic Euler equation. As can be seen from equation (14), an increase in the real risk-free rate r_t on the right-hand-side drives down the output gap x_t on the left-hand side. Intuitively, faced with a higher return to savings, consumers postpone consumption. Because in an economy with sticky prices output is demand-determined, both output and consumption must fall and a recession ensues. Again, the habit coefficients θ_1 and θ_2 are needed for the backward-looking term in the New Keynesian Euler equation and the hump-shaped response.

The large stock risk premium response in the bottom-left panel of Figure 3 is a significant achievement in our model. To understand the stock response recall that dividends are determined by consumption and output in this model, so it is natural that the stock response follows the sign of the output gap response. Stocks drop upon impact and then subsequently recover slowly. Because the depicted returns are cumulative relative to the pre-shock period, this means that stocks experience highly negative returns in the shock period, followed by positive, persistent, but small returns thereafter. Decomposing model stock returns, we see that a positive monetary policy shock drives down stock prices through both the risk-neutral and risk premium components, leading to a larger drop overall. Intuitively, the increase in interest rates and the fall in expected consumption and dividends lower the risk-neutral valuation of stocks. As consumption falls towards habit, investors become more risk averse, lowering stock prices more than the risk-neutral change.

The large and persistent drop in the overall model stock price contrasts with the much less persistent changes in the output gap and real rate used to discount future dividends. Why do model stock returns move so much in response to short-term monetary policy news? This persistence in risk premia arises because the model produces persistent shifts in the surplus consumption ratio, even if not the output gap, because habit adjusts slowly to a change in consumption. This persistence is not a free parameter, but it is pinned down by matching the persistence of the quarterly price-dividend ratio.[14] In that sense, we show that the puzzling persistence of asset price responses to monetary policy shocks can be reduced to a different well-known puzzle, namely the persistence of price-dividend ratios in quarterly data.

Finally, the bottom-right panel of Figure 3 shows that 10-year bond yields increase in response to a positive monetary policy shock. Long-term bond yields increase due to the expectations hypothesis, as captured by the risk-neutral component, and due to risk premia. As under the expectations hypothesis long-term rates reflect the average expected short rate over the life of the bond, it is natural that the risk-neutral bond yield response follows the sign of the monetary policy rate. Further, term premia are positive and bonds are risky in our calibration, so as consumption falls towards habit investors require higher expected excess returns and the term premium steepens, driving up long-term bond yields above and beyond the risk-neutral rise. As for stocks, model bond risk premia are driven by the surplus consumption ratio, and are therefore significantly more persistent than the risk-neutral response.

4 Stocks and bonds around high-frequency monetary policy shocks

Having seen that our parsimonious model fits well the quarterly moments in stocks, bonds, and the macroeconomy, we now turn to the new implications for asset prices around high-frequency monetary policy shocks.

[14] In particular, we set the AR(1) parameter for the surplus consumption ratio θ_0 exactly as in Campbell and Cochrane (1999), who chose its value to match the empirical persistence of the price-dividend ratio. Appendix Table A1 shows that the new habit parameters θ_1 and θ_2 leave the persistence of the model price-dividend ratio almost completely unchanged, so θ_0 is still disciplined by the AR(1) coefficient of the price-dividend ratio in our model.

4.1 Aggregate stock market response

Our analysis of high-frequency asset prices starts with the classic relationship between the aggregate stock market and federal funds surprises in narrow windows around monetary policy announcements. The first three columns of Table 4 summarizes and updates key empirical results from Bernanke and Kuttner (2005) for stock market returns around high-frequency monetary policy shocks. Our baseline regression consists of 30 minute stock market returns $r_{mkt,t}^{FOMC}$ onto 30 minute high-frequency federal funds rate shocks implied by the current month fed funds future $\Delta^{FOMC}i_t$:

$$r_{mkt,t}^{FOMC} \quad = \quad b_{mkt,0} + b_{mkt,1}\Delta^{FOMC}i_t + \varepsilon_{mkt,t} \tag{28}$$

We start our sample in 1994, when the Federal Reserve started announcing policy rate changes. The sample consists of all 202 scheduled FOMC announcements between February 1994 and March 2019. To control for the well-known issue that some surprises in the current month fed funds future may merely reflect changes in the timing of rate changes but not long-lasting news about monetary policy, we control for $timing_t$. Bernanke and Kuttner (2005) defined a "timing surprise" as the change in fed funds futures several months out minus the current funds rate surprise. Following their example, we define $timing_t$ based on the Nakamura and Steinsson (2018) monetary policy shock, which has been used in much of the recent literature to measure surprises about monetary policy rates several quarters out. Specifically, $timing_t$ is defined as the difference between the Nakamura and Steinsson (2018) monetary policy shock, which is the first principal component of the 30 minute changes of fed funds futures and Eurodollar rates at horizons up to four quarters, minus the current month fed funds surprise over the same 30 minute interval.[15]

The first column shows that in the data a one percentage point cut in the federal funds rate leads to an approximately three percentage point increase in stock prices within 30 minutes of the policy announcement. Said differently, the downward-sloping relationship in Figure 1 is highly statistically significant. The response is large, compared to a an empirical output response that peaks at around 0.7 of a percentage point within four to six quarters after the shock (Christiano, Eichenbaum, and Evans (1999)). The second column updates Bernanke and Kuttner (2005)'s finding that positive and negative policy surprises affect the stock market symmetrically. The third column shows that when we

[15]The equity return is measured using value-weighted stock market returns from Trade and Quote data (TAQ) in 30 minute windows around FOMC announcement constructed from Trade and Quote data, accessed through WRDS, as described in detail in Appendix F.1. All our monetary policy surprise variables are from Bauer and Swanson (2020). Constants are included in all regressions but are suppressed in the tables.

control for noise in the current-month fed funds surprise due to news about the timing of interest rate changes, the stock response to monetary news increases further. A one percentage point cut in the federal funds rate now leads to a more than six percentage point increase in stock prices, in line with the magnitudes reported by Bauer and Swanson (2020).

The right set of columns in Table 4 show that the model naturally explains the aggregate stock market response to high-frequency federal funds rate surprises. The model-implied stock market response to a one percentage point surprise increase in the federal funds rate is large and very similar to the data at -6.68 percentage points. Decomposing model stock returns into risk neutral and risk premium components reveals the power of endogenously time-varying risk premia. The model attributes 80% of the stock market response to high-frequency monetary policy shocks to time-varying risk premia, and only 20% to the change in the risk-neutral discounted value of future dividends.[16]

Even though time-varying risk premia contribute significantly to the model stock market response to monetary policy shocks, their effect is close to symmetric with respect to positive and negative monetary policy shocks, similarly to the data. We see that the model coefficient on the interaction FF Shock x (FF Shock > 0) is indistinguishable from the data. The model can explain the symmetric response in the data because while risk-premia in the model are volatile and convex, they are not locally kinked for positive vs. negative consumption surprises. Because news shocks on FOMC dates tend to be small on the order of a few basis points, the effects of small positive and negative consumption surprises in the model are very close to symmetric.

4.2 Industry stock return responses

So far, we have seen that the model does a good job matching the aggregate stock market response to high-frequency monetary policy shocks in the data. If endogenously time-varying risk aversion indeed matters for the financial market responses to monetary policy shocks, we would expect the effects to be stronger for cyclical industries as is often discussed in the financial press.[17] The prior literature has generated a host of empirical results for the cross-section of asset returns on FOMC announcement dates, pointing towards the conclusion that the conditional CAPM is a good description of the cross-section of stock returns on those particular dates (see Figure 5 of Bernanke and Kuttner (2005)) and that value and size factors are not relevant on those event dates, suggesting

[16]The risk-neutral response accounts for both the effects of lower future expected dividends and the higher risk-neutral real rate used to discount these future dividends.

[17]For example on January 5, 2022 Forbes titled "Tech Stocks Feel The Pain As Fed Plans Rate Hikes In 2022" (Forbes, January 5, 2022).

that fundamental news dominates on those dates (Savor and Wilson (2014), Wachter and Zhu (2021)).

Figure 4 and Table 5 show that the responses of industry portfolios to monetary policy shocks line up closely with their unconditional betas, both in the model and in the data. Note that the unconditional stock market beta does does not use FOMC high-frequency data, so the empirical result is not mechanical. The red asterisks with 95% confidence intervals update and sharpen the industry results of Bernanke and Kuttner (2005) using intraday returns. In the data, we regress 30 minute industry returns onto monetary policy shocks in regressions of the form (28) while controlling for $timing_t$ and report the coefficient $b_{1,j}$ for industry j on the y-axis. We see that this high-frequency coefficient lines up closely against the industry's unconditional stock market beta as a measure of industry cyclicality on the x-axis. In Appendix F.1, we confirm that the cross-sectional results are not specific to industry portfolios, but instead look similar for beta-sorted portfolios, thereby isolating cyclicality from other industry characteristics such as duration or financial constraints (Ottonello and Winberry (2020)).

The model matches the relationship between high-frequency regression coefficients and unconditional industry betas in the data, as can be seen from the blue dots. The intuition goes back to the analytic expression for the risk premium on a one-period consumption claim (27). In this expression, a higher cash flow-consumption covariance scales the entire right-hand-side, suggesting that the model risk premium response to a monetary policy shock scales proportionately with the unconditional cash flow beta of each industry. As a result, the model high-frequency coefficient for industry $b_{1,j}$ matches closely the market high-frequency coefficient $b_{1,mkt}$ scaled by industry j's unconditional beta, indicated by the dashed line labeled "CAPM" in Figure 4. The only statistically significant difference between the model and the data arises for the durables sector. This is unsurprising, because our simple model captures only differences in cash flow cyclicality but not duration across industries. Overall, the analysis of industry stock returns around high-frequency monetary policy shocks confirms that endogenously time-varying risk premia can explain this important cross-section around monetary policy news.

4.3 Stock market and industry responses across the risk cycle

Our model of endogenously time-varying risk aversion generates the unique prediction that a positive monetary policy shock should drive down stocks more when the economy is in a high risk aversion state, because this is when model risk aversion is high and volatile. Figure 5 visualizes this model prediction, running the high-frequency regression (28) separately on ten equal-sized subsamples by the risk aversion state variable s_t on model-simulated data. The surplus consumption ratio decile is shown on the x-axis, with lower surplus consumption corresponding to higher risk aversion. We show the overall model regression coefficient in black, the model regression coefficient for risk-neutral stock returns in red dashed, and the model regression coefficient for the risk premium component of stock returns as a blue dotted line. The red dashed line is flat across surplus consumption deciles, so the risk neutral impact of a monetary policy shock on stocks is independent of the risk aversion state in the model. By contrast, the blue dotted line is strongly upward-sloping, indicating that in the model a positive monetary policy shock leads to a larger stock market decline due to larger endogenous risk premia when the economy is a high risk aversion state.

Table 6 shows that the model matches the state-contingent response both for the market and cyclical vs. acyclical industries beautifully. We run regressions of the form

$$\begin{aligned} r_{j,t}^{FOMC} &= b_{j,0} + b_{j,1}\Delta^{FOMC} i_t + b_{j,2}\Delta^{FOMC} i_t \times (RA_t > Median) \\ &\quad + b_{j,3}(RA_t > Median) + \varepsilon_{j,t}, \end{aligned} \tag{29}$$

where j can either stand for the aggregate market or an industry. The key coefficient is $b_{j,2}$ onto the interaction of the monetary policy shock with a dummy indicating high risk aversion RA_t. In the data, we use the VIX to proxy for high risk aversion RA_t while in the model we use the negative surplus consumption ratio.[18]

The first column in the top panel shows that the interaction coefficient $b_{mkt,2}$ for the overall stock market is negative and significant in the data. Both the direct coefficient $b_{mkt,1}$ and the interaction coefficient $b_{mkt,2}$ in the empirical regressions are similar to the corresponding model regressions shown in the bottom panel. The next columns show that the interaction coefficient increases monotonically from less cyclical (utilities) to more cyclical (high-tech) industries sorted from left to right. This monotonicity is again qualitatively and quantitatively in line with the model regressions in the bottom panel, confirming the model prediction that time-varying risk premia scale up for portfolios that have a higher unconditional cash flow-consumption covariance. Overall, the model prediction that stocks should respond more strongly to monetary policy shocks in high risk aversion states is borne out in aggregate and industry stock return data.

[18]We use the VIX as a risk aversion state variable in our empirical analysis because, unlike the dividend price ratio it is not subject to a persistent levels shift in the late 1990s. In Appendix F.2 we show that empirical results are similar if we replace the VIX dummy with a continuous VIX variable, and verify robustness to using the dividend price ratio in a post-2002 sample.

4.4 Bond yield responses

We next use our model to show that our central channel – endogenous variation in risk aversion – can also generate large responses in nominal and especially real long-term bond yields to monetary policy shocks, in line with the data. As documented by Hanson and Stein (2015) and Nakamura and Steinsson (2018), real and nominal long-term bond yields respond surprisingly strongly to a monetary policy surprise in the data, and more than can be rationalized in a New Keynesian model with typical policy rate persistence and constant risk aversion.

The top panel of Table 7 updates and summarizes the existing empirical evidence of long-term bond yield responses to monetary policy surprises. We run empirical regressions of daily changes in 10-year long-term bond yields onto several measures of monetary policy surprises:

$$\Delta^{FOMC} y_{n,t} = b_{n,0} + b_{n,1} Shock_t + \varepsilon_{n,t}. \tag{30}$$

Here, the monetary policy shock $Shock_t$ can be the fed funds change implied by the current month futures, as in our analysis of stock returns, the fed funds change implied by the three month futures as in Gertler and Karadi (2015), or the Nakamura and Steinsson (2018) monetary policy shock. We use a number of monetary policy shocks with different maturities to account for findings in the empirical literature that bond yields respond most strongly to forward guidance monetary policy shocks. We measure $\Delta^{FOMC} y_{n,t}$ using one-day changes in zero-coupon bond yields from Gürkaynak, Sack, and Wright (2007) and Gürkaynak, Sack, and Wright (2010). Changes in breakeven inflation are defined as the difference between the daily change in the nominal minus the real (or inflation-indexed) bond yield.[19]

We see that in the data long-term bond yields respond strongly to monetary policy shocks, with generally larger responses for real than for nominal long-term bond yields, and negative but insignificant declines in breakeven inflation. We also confirm previous findings that empirical bond yield responses are larger for more forward-looking monetary policy shocks. The bond yield responses to the Nakamura and Steinsson (2018) monetary policy shock are particularly large, with a 100 bps increase in that monetary policy shock typically leading to a 68 bps increase in the 10-year nominal government bond yield, a 74 bps increase in the real government bond yield, and a -11 bps but statistically insignificant

[19]We use a shorter sample for changes in real yields and breakeven starting when they become available in 1999. The first three columns in Table 7 do not control for $timing_t$. In unreported results we verified that controlling for $timing_t$ in the first three columns leads to empirical estimates very similar to the regression results using the Nakamura and Steinsson (2018) shock reported in the last three columns of the same table.

decline in 10-year breakeven. Given that nominal product prices are unlikely to be sticky over a 10-year time horizon, these empirical results raise the question to what extent they can be understood within New Keynesian models of monetary policy.

The lower three panels of Table 7 run analogous regressions in the model and show that it can generate large bond yield responses, partly thanks to time-varying risk premia. We start the model analysis with our baseline calibration with $\kappa = 0$, i.e. perfectly sticky prices. In this case, real and nominal bonds are identical and the breakeven response to monetary policy shocks is naturally zero. The second panel of Table 7 shows that in this case the model produces a sizeable long-term bond yield response to a monetary policy shock, explaining most of the empirical responses to the current month or 3 month fed funds futures surprise, and a significant fraction of the empirical responses to the Nakamura and Steinsson (2018) shock. The time-varying risk premium component of long-term bond yields is important for this success, as it is responsible for more than half of the model bond yield response. The decomposition into risk-neutral and risk premium responses therefore indicates that the endogenous time-variation in risk aversion that is new relative to the standard New Keynesian model can help explain the large responses of long-term bond yields in the data.

The model mechanism is intuitive and relies on the same endogenous change in risk aversion that also explains stock returns around monetary policy shocks in our model. As noted in the discussion of the cross-section of industry returns, in our model any asset that requires a positive unconditional risk premium will require a higher risk premium when risk aversion rises, as after a contractionary monetary policy shock. Precisely because the model matches the unconditional slope of the term structure, the endogenous rise in risk aversion from a monetary policy shock further raises bond risk premia, generating the large increase in long-term bond yields in the bottom Panel of Table 7.

We next investigate the role of product price flexibility and how it affects the responses of nominal and real bond yields to monetary policy shocks in the model. We compare the same model regressions across different values for the Phillips curve slope parameter, κ, where a higher value of κ corresponds to more flexible nominal product prices. We consider a Phillips curve parameter of $\kappa = 0.0554$, corresponding to a textbook value for the quarterly probability of keeping prices fixed of 2/3, and a small but nonzero value of $\kappa = 0.0045$, which is similar to the Phillips curve slope estimated by Nakamura and Steinsson (2018) and corresponds to a quarterly probability of no price adjustment of 0.9.[20] Maybe surprisingly, and counter to the intuition verbalized in Hanson and Stein

[20]We also use backward- and forward-looking coefficients in the Phillips curve of $\rho^\pi = 0.51$ and $f^\pi = 0.49$. These values for κ and ρ^π are consistent with the stated probabilities of price adjustment assuming a textbook value for the Frisch elasticity equal to one, a capital share of production equal to 1/3, and the cross-goods elasticity of substitution of 6, following Galí (2008). We also assume a monetary

(2015), we find that more flexible nominal prices (i.e. larger κ) may actually *increase* the response of real long-term bond yields to a positive monetary policy shock. The intuition is that when prices are flexible, a surprise hike in the policy rate leads to a decline in output and – through the Phillips curve – lower inflation expectations. Because the rule for the nominal policy rate is the same for all values of κ, the decline in inflation expectations must lead to a larger increase in long-term real bond yields.

With imperfectly sticky prices ($\kappa > 0$), the larger real bond yield-monetary policy shock coefficient is further amplified by time-varying risk premia, suggesting that time-varying risk premia can help explain why real long-term bond yields respond strongly to monetary policy shocks when prices are not perfectly sticky. The intuition is that when $\kappa > 0$ the expected real rate rises more and bond prices fall more just as marginal utility increases, making real bonds risky. Because real bonds are riskier with $\kappa > 0$, real long-term bond risk premia increase more as risk aversion increases following a positive monetary policy surprise.

One caveat in our analysis of long-term bonds is that both the unconditional term structure and the response of long-term bond yields to monetary policy shocks in the model require bonds to be risky. In the model, bonds have moderately risky payoffs because a positive monetary policy shock drives up marginal consumption utility, raises bond yields, and drives down bond prices. Bonds being risky is consistent with the upward-sloping term structure. The baseline model bond-stock beta of around 0.23 is in line with bond-stock betas during the mid-1990s, but it does not capture the negative bond-stock betas during the 2000s (Campbell, Pflueger, and Viceira (2020)). However, investors might not have immediately understood this change in bond-stock betas or might have expected the economy to revert to a positive bond-beta regime.[21] We conclude that the endogenous increase in risk aversion to a positive monetary policy shock can explain economically large increases in bond risk premia, provided that bonds are risky and match the upward-sloping term structure.

5 Conclusion

We show that the same business cycle variation in risk aversion that rationalizes standard asset pricing facts can also explain many new empirical findings of stocks and bonds

policy inflation coefficient of $\gamma^{\pi} = 1.5$ as in Taylor (1993). For details of how Phillips curve parameters are derived from microfoundations see Appendix B.3.

[21] Song (2017) shows that an upward-sloping term structure and negative bond-stock betas can be reconciled in a regime-switching model, though he does not consider a micro-founded New Keynesian model or monetary policy shocks. To keep the model as parsimonious and disciplined as possible we do not pursue a regime-switching model here.

around high-frequency monetary policy shocks. Our model integrates the smallest-scale standard New Keynesian model of monetary policy with countercyclical risk premia using the habit formation preferences of Campbell, Pflueger, and Viceira (2020). We calibrate our model to the empirical consumption volatility and the unconditional low-frequency response of output to monetary policy news, and show that it fits the low-frequency moments of stocks and bonds, such as the aggregate stock return volatility, the persistence of the price-dividend ratio, predictability of stock returns, and the slope of the term structure.

Even though not targeted explicitly in the calibration, the model gives a natural and quantitatively realistic picture of stocks and bonds around monetary policy surprises. The model generates a large decline in the stock market following a surprise increase in the fed funds rate, despite a small and empirically realistic output response. The reason is that bad economic news, such as a contractionary monetary policy shock, drives consumption down towards habit and makes investors more risk averse, thereby lowering their valuations of risky stocks. We go further and show that our parsimonious one-shock model does a surprisingly good job in rationalizing a host of other empirical facts around monetary policy news announcements. It naturally explains why cyclical industry stocks fall more in response to a surprise increase in the fed funds rate, and also why stocks seem to respond more to monetary policy in states of the world when risk aversion is already high. Further, it can generate large response in long-term real bond yields through endogenously time-varying risk aversion.

Our model can therefore be interpreted as saying that the famous equity volatility puzzle of Shiller (1981) and the large stock response to monetary policy news of Bernanke and Kuttner (2005) are two sides of the same coin. In short, many empirical findings can be reconciled if monetary policy moves the macroeconomy and therefore risk aversion. This mechanism has implications for researchers and policy makers, who use financial market prices to estimate how monetary policy affects the economy, because it implies that financial market responses can be significantly amplified due to endogenously time-varying risk premia.

Our framework is tractable and portable towards broader macroeconomic models as well as a greater variety of shocks. On the macroeconomic side, we anticipate that our model serve as a tool to impose financial markets discipline on macroeconomic drivers beyond the channels considered in this basic macroeconomic model, such as wage rigidities or heterogeneity in price-setting frictions (Weber (2015)). On the asset pricing side, we believe that it will be fruitful to build on our model to understand the role of time-varying risk premia in other empirical puzzles, such as the empirical finding that equity returns are typically high prior to FOMC dates (Lucca and Moench (2015), Cieslak, Morse, and Vissing-Jorgensen (2019), Cieslak and Pang (2021)) or the empirical fact that good macroeconomic news is sometimes bad news for stocks (Boyd, Hu, and Jagannathan (2005), Law, Song, and Yaron (2019)).

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Table 1: Model Parameters

Parameter			Source	Empirical Target
Preferences:				
Consumption Growth Rate	g	1.89	Campbell and Cochrane (1999)	Average consumption growth
Utility Curvature	γ	2.00	Campbell and Cochrane (1999)	Equity Sharpe ratio
Steady-State Riskfree Rate	$\bar{r}$	0.94	Campbell and Cochrane (1999)	Average real risk-free rate
Persistence Surplus Consumption	θ_0	0.87	Campbell and Cochrane (1999)	AR(1) price-dividend ratio
Surplus Consumption - Output Gap	θ_1	-0.95	Directly matched to moment	Lag output response to MP shock
Monetary Policy:				
MP Coeff. Output	γ^x	0.50	Taylor (1993)	Reduced-form regression
MP Persistence	ρ^i	0.80	Clarida, Gali, and Gertler (2000)	Reduced-form regression
Std. Quarterly MP Shock (%)	σ_{MP}	1.19	Directly matched to moment	Std. annual consumption growth
Std. FOMC News Shocks(%)	σ_{MP}^{FOMC}	6.52 bps	Directly matched to moment	Std. thirty-minute fed funds surprises
Consumption and Dividends:				
Consumption-Output Gap Link	ϕ	0.93	Campbell, Pflueger, and Viceira (2020)	Corr(output gap, detrended consumption)
Leverage	δ	0.67	Directly matched to moment	Std. stock returns

Note: This table shows the model parameter values and the papers in the literature that the parameter values are drawn from. The "Empirical Target" column lists the moment in the data that the literature has targeted with this parameter, if the parameter is taken from the literature, or the moment that we match if the parameter is directly matched to the data. Consumption growth and the steady-state risk-free rate are in annualized percent. The persistence of surplus consumption is annualized. The monetary policy coefficient is in units corresponding to our empirical variables, i.e. the log output gap is in percent and the fed funds rate is in annualized percent. We report the quarterly standard deviation of shocks to the annualized percent fed funds rate.

Table 2: Implied Model Parameters

Discount Rate	β	0.90
Steady-State Surplus Consumption Ratio	$\bar{S}$	0.03
Maximum Surplus Consumption Ratio	S^{max}	0.05
Euler Equation Lag Coeff.	ρ^x	0.47
Euler Equation Forward Coeff.	f^x	0.53
Euler Equation Real Rate Slope	ψ	0.07
Surplus Consumption - Lagged Output Gap	θ_2	0.88

Note: This table shows model parameters implied by the calibration. The discount rate is annualized. The implied Euler equation real rate slope is reported as $\frac{1}{4}\psi$ to match that interest rates are typically reported in annualized percent.

Table 3: Unconditional Quarterly Model Properties

Stocks		Model	Data
	Equity Premium	7.63	7.84
	Volatility	15.61	16.87
	Sharpe Ratio	0.49	0.47
	AR(1) Coeff. pd	0.95	0.92
	1-YR Excess Returns on pd	-0.27	-0.38
	1-YR Excess Returns on pd (R^2)	0.06	0.23
10-Year Nominal Bonds			
	Yield Spread	1.12	1.87
	Volatility Excess Returns	3.65	9.35
	1-YR Excess Returns on Yield Spread	-0.27	2.69
	1-YR Excess Returns on Yield Spread (R^2)	0.01	0.14
Macroeconomic Dynamics			
	Std. Annual Cons. Growth	1.54	1.50
	Std. Annual Change fed funds Rate	2.12	1.35
	Trough Output Response to 100 bps fed funds Surprise	-0.72	-0.7
	Lag Trough Output Response	4 Quarters	4-6 Quarters

Note: This table reports the unconditional asset pricing moments in actual and model-simulated data. Unless otherwise noted, empirical moments are from our own calculations for the sample 1994Q1-2019Q1. The equity premium is computed as the quarterly log return on the value-weighted combined NYSE/AMEX/Nasdaq stock return including dividends from CRSP in excess of the log 3-month Treasury bill plus one-half times the log excess return variance to adjust for Jensen's inequality. Bond excess returns are quarterly log returns on 10-year Treasury bonds in excess of the log nominal 3-month Treasury bill return. We compute empirical log returns on the 10-year nominal Treasury bond from log bond yields: $r^{\$}_{n,t} = -(n-1)y^{\$}_{n-1,t} + ny^{\$}_{n,t}$. We obtain continuously compounded 10-year zero-coupon yields from Gürkaynak, Sack, and Wright (2007). Excess returns and volatilities are in annualized percent. The size and lag of the empirical output response to a monetary policy shock are from Christiano, Eichenbaum, and Evans (1999). The empirical standard deviation of annual consumption growth is from Campbell and Cochrane (1999). Model moments follows the same procedures as above on simulated data and are from a simulation of length 10000.

Table 4: Stock Market onto High-Frequency Monetary Policy Shocks

	Data			Model: Overall		Model: Risk Neutral		Model: Risk Premium	
FF Shock	-3.02***	-2.73*	-6.14***	-6.68	-6.62	-1.56	-1.56	-5.12	-5.06
	(0.99)	(1.53)	(1.16)						
FF Shock x (FF Shock >0)		0.54			-0.07		0.00		-0.07
		(2.14)							
Timing			-5.67***						
			(1.52)						

Note: This table compares the stock market response to monetary policy shocks in actual and model-simulated data. The first three columns use an empirical sample of 202 scheduled FOMC announcements from February 1994 until March 2019 and run regressions of the form $r^{FOMC}_{mkt,t} = b_{mkt,0} + b_{mkt,1}\Delta^{FOMC} i_t + \varepsilon_{mkt,t}$, where $r^{FOMC}_{mkt,t}$ is the value-weighted stock market return within 30 minutes around FOMC announcements computed from Trade and Quote (TAQ) data. The monetary policy shock $\Delta^{FOMC} i_t$ is the fed funds surprise implied by the change in the current month futures over the same time interval. The second column includes the same monetary policy shock interacted with a dummy taking a value of one if the shock is positive, and zero otherwise. The third column includes $timing_t$, defined as the difference between Nakamura and Steinsson (2018) monetary policy shock minus $\Delta^{FOMC} i_t$, to control for news that primarily represent a shift in the timing of policy rate changes. Heteroskedasticity adjusted standard errors are reported in parentheses below the empirical estimates. Model regressions are run analogously on a simulated sample of length 10000. Risk-neutral stock prices are computed with the risk-neutral discount factor that is consistent with equilibrium dynamics for the real interest rate. Risk neutral and risk premium stock returns add up to the overall model stock return. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Industry Stock Returns onto High-Frequency Monetary Policy Shocks

	Utils	NoDur	Hlth	Enrgy	Shops	Telcm	Manuf	Other	Durbl	HiTec
Data										
FF Shock Coeff.	-4.34***	-4.78***	-4.35***	-4.86***	-5.73***	-6.18***	-5.97***	-7.18***	-5.63***	-7.02***
	(0.87)	(0.81)	(1.00)	(1.22)	(1.12)	(1.34)	(1.15)	(1.65)	(1.12)	(1.32)
Quarterly Beta	0.45	0.65	0.65	0.73	0.83	0.95	0.98	1.04	1.24	1.39
	(0.08)	(0.06)	(0.06)	(0.09)	(0.05)	(0.07)	(0.05)	(0.05)	(0.09)	(0.07)
Model										
FF Shock Coeff.	-3.01	-4.34	-4.34	-4.80	-5.55	-6.35	-6.55	-6.95	-8.29	-9.29
Quarterly Beta	0.46	0.66	0.66	0.73	0.83	0.95	0.98	1.04	1.24	1.39

Note: For industry j we report the coefficient $b_{j,1}$ from the regression $r_{j,t}^{FOMC} = b_{j,0} + b_{j,1}\Delta^{FOMC} i_t + b_{j,2} timing_t + \varepsilon_{j,t}$. Here, $r_{j,t}^{FOMC}$ is the 30 minute industry return around FOMC announcements from TAQ. Industries are sorted by their quarterly stock market beta from left to right. Quarterly betas are the regression coefficients of quarterly (i.e. not high-frequency) industry returns onto the market returns $r_{j,t+1} = \alpha_j + \beta_j r_{mkt,t+1} + \varepsilon_{j,t+1}$ with robust standard errors. All other variables and the sample are defined in Table 4. Heteroskedasticity adjusted standard errors are reported in parentheses below the empirical estimates. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Stock Returns onto High-Frequency Monetary Policy Shocks by Risk Aversion

	Mkt	Utils	NoDur	Hlth	Enrgy	Shops	Telcm	Manuf	Other	Durbl	HiTec
Data - High-Frequency Regression											
FF Shock	-4.14***	-4.33***	-3.79***	-2.94**	-3.26***	-4.30***	-4.78***	-3.99***	-4.43***	-3.97***	-4.65***
	(1.14)	(0.76)	(0.92)	(1.21)	(1.04)	(1.17)	(1.23)	(1.08)	(1.48)	(1.18)	(1.36)
FF Shock (RA_t >Med)	-3.25**	-0.18	-1.68	-2.26	-2.74*	-2.43*	-2.37	-3.15**	-4.38**	-2.74*	-3.86**
	(1.57)	(1.17)	(1.14)	(1.51)	(1.51)	(1.46)	(1.52)	(1.43)	(2.15)	(1.43)	(1.88)
Model - High-Frequency Regression											
FF Shock	-5.72	-2.58	-3.72	-3.72	-4.18	-4.75	-5.44	-5.61	-5.95	-7.10	-7.96
FF Shock (RA_t >Med)	-1.93	-0.87	-1.26	-1.26	-1.41	-1.60	-1.84	-1.89	-2.01	-2.40	-2.69
Empirical Quarterly Beta											
	1	0.45	0.65	0.65	0.73	0.83	0.95	0.98	1.04	1.24	1.39
	(0.00)	(0.08)	(0.06)	(0.06)	(0.09)	(0.05)	(0.07)	(0.05)	(0.05)	(0.09)	(0.07)

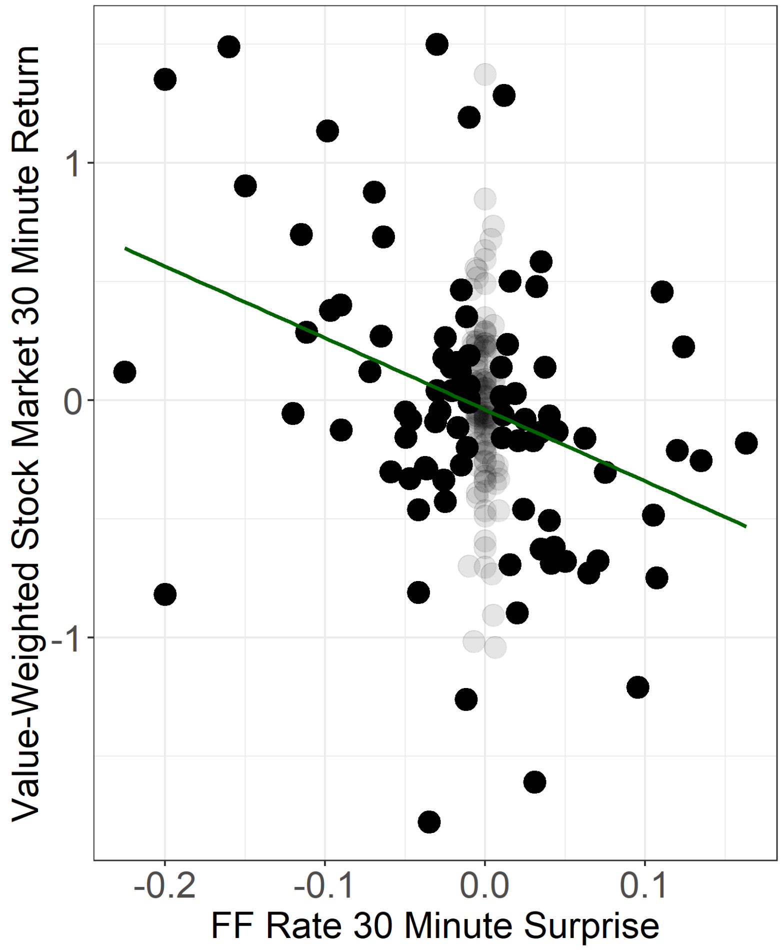
Note: This table reports regressions of the form $r_{j,t}^{FOMC} = b_{j,0} + b_{j,1}\Delta^{FOMC} i_t + b_{j,2}\Delta^{FOMC} i_t (RA_t > Median) + b_{j,3}(RA_t > Median) + b_{j,4} timing_t + \varepsilon_{j,t}$. Here, $r_{j,t}^{FOMC}$ is the 30 minute industry or market return around FOMC announcements computed from TAQ data. In the data, we use the VIX to proxy for high risk aversion RA_t while in the model we use the negative surplus consumption ratio. The constant, the dummy coefficient, and the timing control are suppressed in the table. Industries are sorted by their quarterly stock market beta from left to right. All other variables and the sample are as in Tables 4 and 5. Heteroskedasticity adjusted standard errors are reported in parentheses below the empirical estimates. *p<0.1; **p<0.05; ***p<0.01.

Table 7: 10-Year Bond Yields onto High-Frequency Monetary Policy Shocks

	Surprise: Fed Funds			*Surprise: 3M Fed Funds Futures*			*Surprise: Nakamura-Steinsson*		
	Nominal	Real	Bkeven	Nominal	Real	Bkeven	Nominal	Real	Bkeven
Data	0.04	0.26*	-0.14	0.25*	0.39**	-0.09	0.68***	0.74***	-0.11
	(0.12)	(0.14)	(0.09)	(0.14)	(0.18)	(0.11)	(0.14)	(0.17)	(0.10)
Model: Phillips curve slope $\kappa = 0$									
Model Overall	0.16	0.16	0.00	0.21	0.21	0.00	0.22	0.22	0.00
Risk Neutral	0.07	0.07	0.00	0.10	0.10	0.00	0.10	0.10	0.00
Risk Premium	0.09	0.09	0.00	0.12	0.12	0.00	0.12	0.12	0.00
Model: Phillips curve slope $\kappa = 0.0045$									
Model Overall	0.08	0.16	-0.08	0.11	0.21	-0.10	0.12	0.24	-0.11
Risk Neutral	0.03	0.07	-0.04	0.04	0.09	-0.05	0.05	0.11	-0.06
Risk Premium	0.05	0.09	-0.04	0.07	0.12	-0.05	0.08	0.13	-0.06
Model: Phillips curve slope $\kappa = 0.0554$									
Model Overall	0.04	0.17	-0.13	0.06	0.27	-0.21	0.07	0.33	-0.26
Risk Neutral	0.02	0.07	-0.06	0.03	0.12	-0.09	0.03	0.15	-0.11
Risk Premium	0.02	0.1	-0.08	0.03	0.15	-0.12	0.04	0.18	-0.15

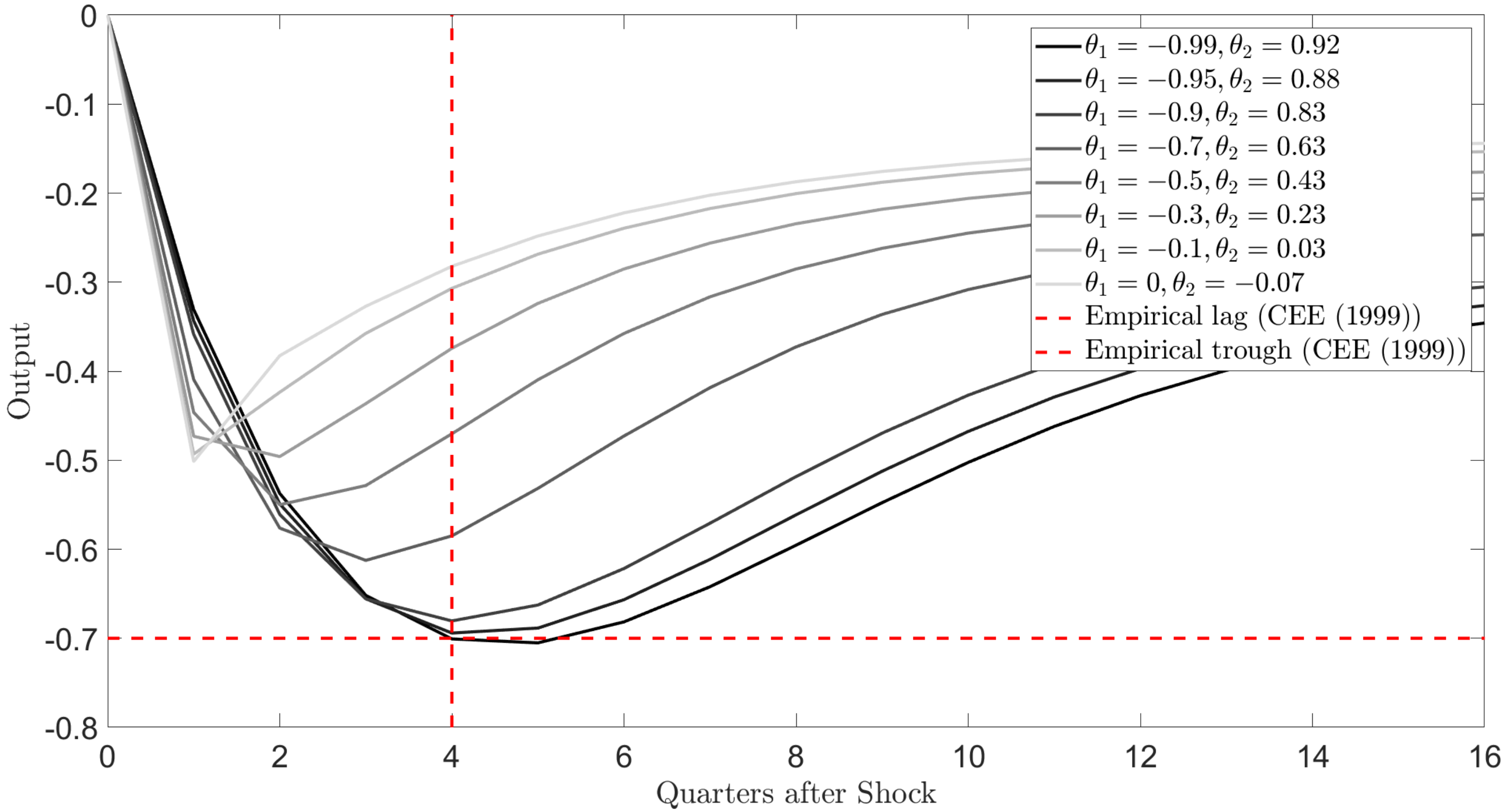
Note: This table reports the slope coefficient $b_{n,1}$ from regressions of the form $\Delta^{FOMC} y_{n,t} = b_{n,0} + b_{n,1} Shock_t + \varepsilon_{n,t}$ using different measures for the monetary policy shock, $Shock_t$. The first three columns use the fed funds surprise implied by the current month futures. The middle three columns use the fed funds surprise from the three month futures as in Gertler and Karadi (2015). The last three columns use the high-frequency shock of Nakamura and Steinsson (2018), which is the first principal component of 30-minute changes in fed funds futures and Eurodollar rates with maturities of up to one year. The sample consists of all scheduled FOMC announcements from January 1994 until March 2019 for nominal bonds. The real bond yield regressions and breakeven (defined as nominal minus real yields) start in 1999 when TIPS yields become available. Note that the breakeven and real bond yield coefficients do not need to sum up to the nominal coefficient because the nominal regressions use a longer sample. $\Delta^{FOMC} y_{n,t}$ is measured using daily changes in zero-coupon yields from Gürkaynak, Sack, and Wright (2007) and Gürkaynak, Sack, and Wright (2010). "Model Overall" reports analogous regression on model simulated data. "Model Risk Neutral" uses the risk neutral component of bond yields on the left-hand-side. "Model Risk Premium" regresses the risk premium component of bond yields onto the monetary policy surprises. Risk neutral bond yields are the asset prices that would obtain under a risk neutral investor taking macroeconomic dynamics as given, and correspond to the expectations hypothesis. The risk premium component of bond yields is the difference between the overall yield minus the risk neutral yield. In the model we proxy for the Nakamura and Steinsson (2018) shock with the instantaneous change in the nominal one-year Treasury bond yield. Heteroskedasticity adjusted standard errors are reported in parentheses below the empirical estimates. *p<0.1; **p<0.05; ***p<0.01

Figure 1: Stock Returns and the Federal Funds Rate on FOMC Dates



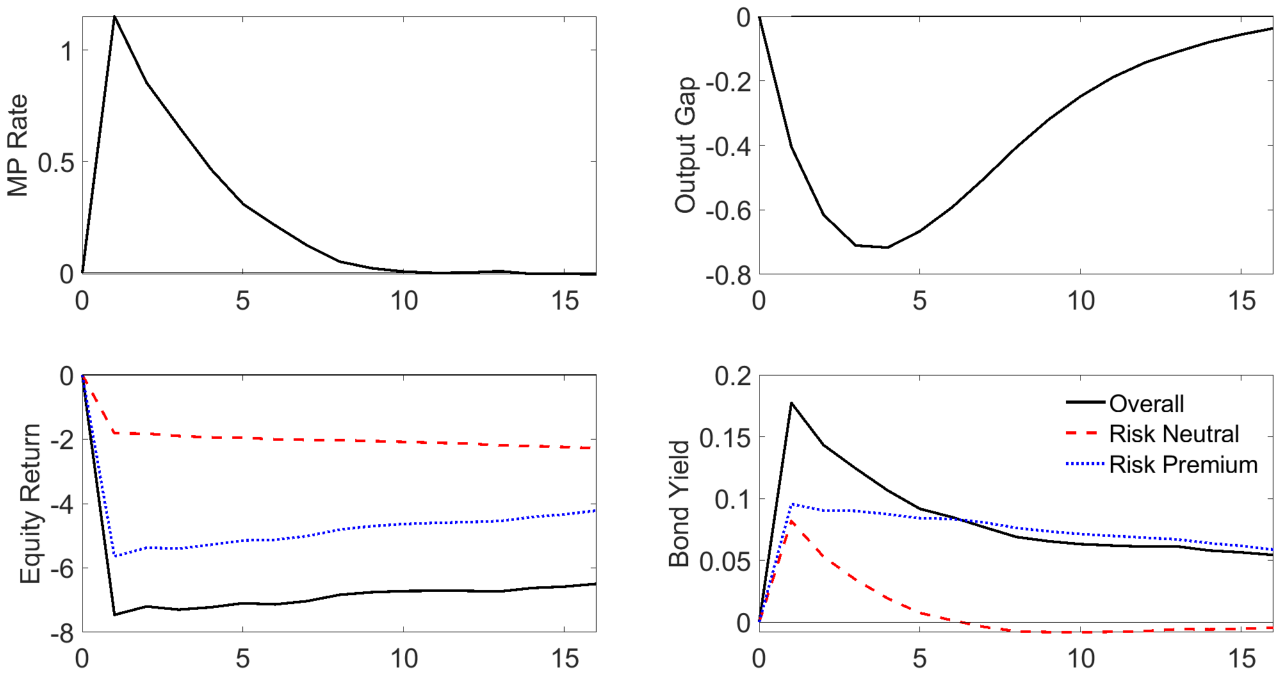
Note: This figure shows the relationship of federal funds rates surprises in a 30 minute window around FOMC announcements against 30 minute value-weighted stock market returns computed from TAQ data. Each data point corresponds to a FOMC meeting. We show a linear regression best fit line. FOMC days where the absolute federal funds rate surprise was less than 1 basis point are shown in gray. The sample consists of 202 scheduled FOMC dates from February 1994 until March 2019.

Figure 2: Model Output Response for Different Habit Parameters



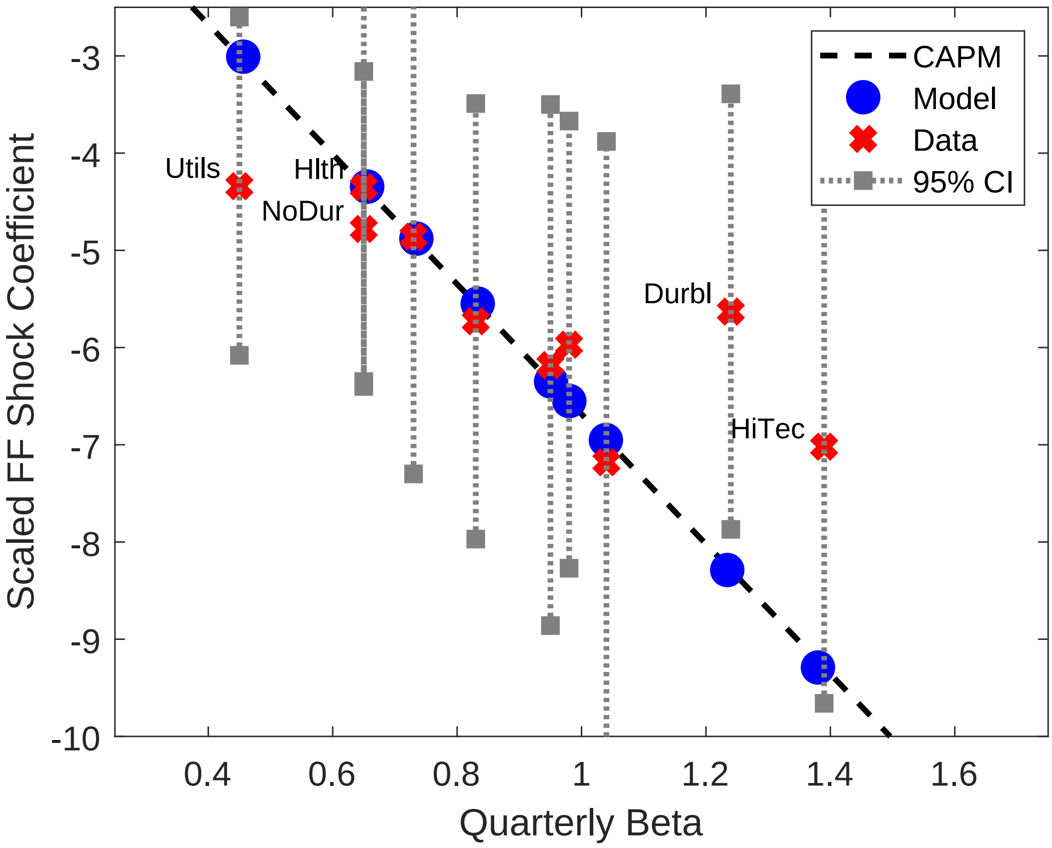
Note: This figure shows the output impulse response to a 100 bps monetary policy shock at different values of the habit parameter θ_1. Each line corresponds to a different value of θ_1, and the implied values for θ_2 are determined by the restriction that the coefficients in the New Keynesian Euler equation sum up to one, i.e. equation (16). The horizontal axis shows the number of quarters after the short-term monetary policy shock. The y-axis shows output as a percent deviation from initial value. Red dashed lines show the empirical trough response and the lag of the empirical trough from Christiano, Eichenbaum, and Evans (1999).

Figure 3: Model Asset Price Responses to Monetary Policy Shock



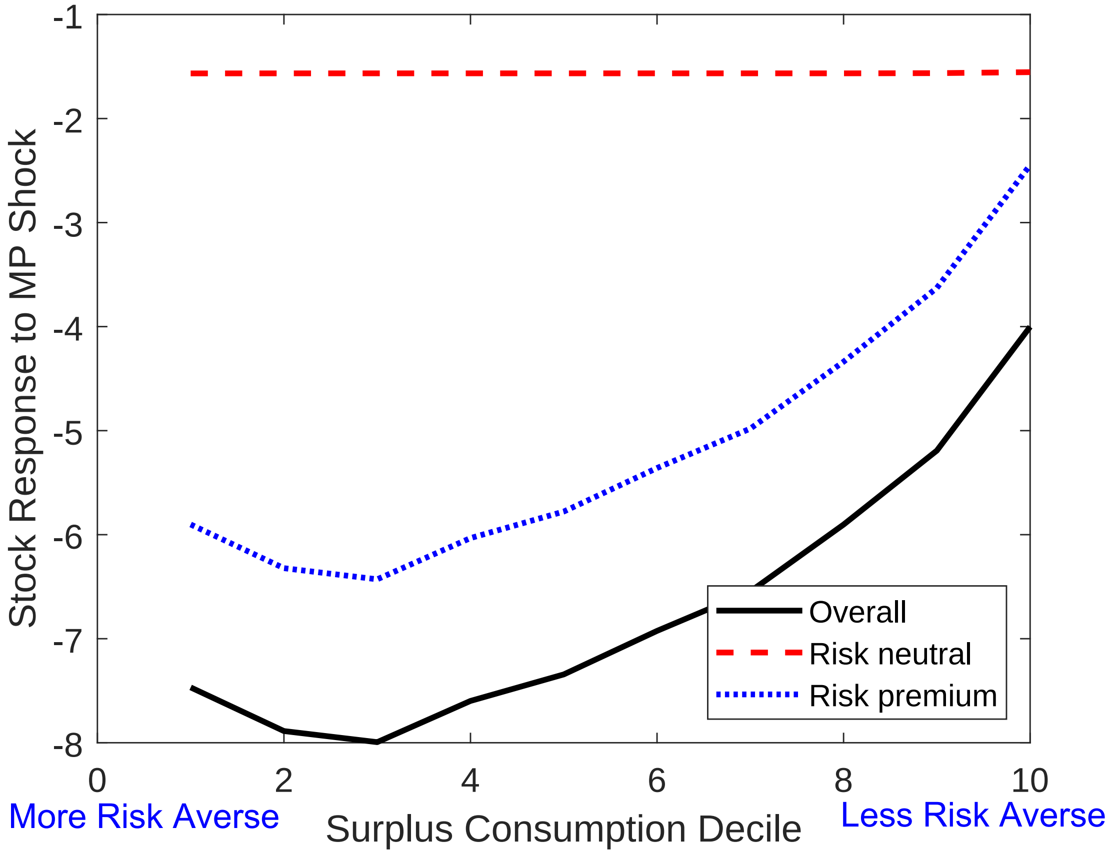
Note: This figure shows the model impulse responses to a one-standard deviation monetary policy shock. The first row shows the macroeconomic responses of the federal funds rate in annualized percent and the output gap in percent. The second row shows the responses of unexpected equity returns in percent and bond yields in annualized percent, respectively. The stock return is cumulative from the pre-shock period and in excess of the steady state equity return. Risk-neutral stock and bond prices are computed through the same recursions with the risk-neutral discount factor that is consistent with equilibrium dynamics for the real interest rate. Risk neutral and risk premium components add up to the total response. The horizontal axis of each panel shows the number of quarters after the shock. Impulse responses are averaged over 5000 independent simulations around the stochastic steady-state.

Figure 4: Industry Returns onto High-Frequency Monetary Policy Shocks



Note: This figure shows the high-frequency regression coefficients $b_{j,1}$ for each industry j from a regression $r_{j,t}^{FOMC} = b_{j,0} + b_{j,1}\Delta^{FOMC} i_t + b_{j,2} timing_t + \varepsilon_{j,t}$ on the y-axis. The quarterly industry beta, as reported in Table 5, is reported on the x-axis. 95% confidence intervals computed with heteroskedasticity-robust standard errors are shown for the empirical coefficients $b_{j,1}$. Model regressions are run on a simulated sample of length 10000.

Figure 5: Model Stock Returns onto High-Frequency Monetary Policy Shock by Risk Aversion



Note: This figure shows model regressions of the same form as in Table 4 conditional on the model surplus consumption ratio: $r^{FOMC}_{mkt,t} = b_{mkt,0} + b_{mkt,1}\Delta^{FOMC} i_t + \varepsilon_{mkt,t}$. The figure plots the coefficient $b_{mkt,1}$ on the y-axis against surplus consumption deciles on the x-axis from model-simulated data. The simulated data is split into ten sub samples according to the deciles of the log surplus consumption ratio s_t. We plot the coefficients obtained by running the regression separately within each of these ten subsamples. Solid lines use overall equity returns as the left-hand-side variable, dashed lines use risk neutral stock returns, and dotted lines use the risk premium component of stock returns. Risk neutral and risk premium coefficients add up to the overall coefficient. We use a model-simulated sample of length 10000.