What do Treasury Bond Risks Say about Supply and Demand Shocks?*

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Abstract

This paper analyzes how the risks of nominal and inflation-indexed Treasury bonds vary with the presence of supply and demand shocks through the lens of a small-scale New Keynesian model with habit formation preferences, where investors become more risk averse following adverse economic shocks. We calibrate the model separately for the time periods 1979.Q4-2001.Q1 and 2001.Q2-2019.Q4. For the 1980s calibration, volatile supply shocks raise inflation and the Fed responds by raising interest rates, leading to a recession and simultaneous drops in nominal bond and stock prices. For the 2000s calibration, volatile demand shocks lower the output gap and raise interest rates, leading to simultaneous increases in nominal and real bond prices and a stock market downturn. As a result, nominal Treasury bond-stock betas are positive in the 1980s calibration, and negative in the 2000s calibration, as in the data. Counterfactual exercises show that volatile supply shocks alone are not sufficient to generate the high and positive nominal Treasury bond betas of the stagflationary 1980s, but that a monetary policy rule that responds strongly to supply shocks is also needed. Partially backward-looking inflation expectations by wage-setters are important to match the predictability of bond excess returns as in Campbell and Shiller (1991).

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1 Introduction

Did the severe stagflation of the 1980s occur because the economy was subject to supply shocks or because the Volcker Fed raised interest rates and hence engineered a recession? And, given recent supply shocks to oil prices and supply chain disruptions, should we expect a return to a similarly stagflationary regime and risky Treasury bond markets? We show that a New Keynesian asset pricing model with risk aversion linked to the business cycle can explain the broad changes from risky nominal Treasury bonds in the 1980s to safe nominal Treasury bonds and negative bond-stock betas in the 2000s. Further, the model implies that the high risks of nominal Treasury bonds in the 1980s were the result of a "perfect storm" of volatile supply shocks and a monetary policy rule that reacted strongly and immediately to such shocks.

Figure 1 shows that the risks of nominal and inflation-indexed government bonds underwent significant changes along with these macroeconomic changes.[1] Because ten-year nominal bond prices should fall with long-term inflation expectations, they intuitively serve as a good indicator of the inflation risks that the economy faces. In Panel A, we see that nominal ten-year Treasury bonds had strongly positive betas with respect to the stock market, meaning that nominal Treasury bonds tended to fall at the same time as the stock market. Inflation-indexed bonds shared some of these properties but their betas were much smaller in magnitude, indicating a substantial role for inflation expectations. During the 2000s, however, the betas of both nominal and inflation-indexed bonds became negative and the gap narrowed, indicating less volatile inflation expectations that tended to fall along with the stock market. For the first two post-pandemic years 2020.Q1–2022.Q2, perhaps surprisingly, the picture looks markedly different from the 1980s, with inflation-indexed bond betas turning positive, while nominal bond betas remained predominantly negative. We use a simple model of supply and demand shocks with monetary policy and time-varying risk premia to understand these changes in nominal and inflation-indexed bond betas.

We integrate a New Keynesian model with supply and demand shocks with macro-asset pricing habit formation preferences. We build on Campbell et al. (2020) by introducing a new demand shock, which we model as arising from a preference shock for bonds.[2] Most simply,

[1] We regress quarterly bond excess returns onto quarterly stock returns over five-year rolling windows and plot the resulting rolling slope coefficient in Panel A. Panel B shows the slope coefficient of daily bond returns onto daily stock returns post-2018 using six-month rolling windows. We compute bond returns from zero-coupon nominal and inflation-indexed yields, so the bond duration is held constant at ten years. We use UK inflation-linked bond yields prior to 1999 and yields on US Treasury Inflation Protected Securities (TIPS) after 1999, when TIPS data becomes available.

[2] While Campbell et al. (2020) and Pflueger and Rinaldi (2022) make steps toward integrating a simple New Keynesian model with asset prices via habit formation preferences, the published versions of those papers do not feature supply or demand shocks, and therefore they cannot provide a decomposition of bond

a negative 10 bps preference shock means that households make their intertemporal savings decisions as if the policy rate set by the Fed was 10 bps lower than the risk-free rate faced by households. In response to such a shock, consumption and output fall relative to habit, raising the required return on risky stocks. The preference shock can therefore be interpreted as a change in the convenience benefit priced into Treasury bonds (Krishnamurthy and Vissing-Jorgensen (2012), Du et al. (2018a), Du et al. (2018b), Jiang et al. (2021)), preference for safety not immediately driven by aggregate risk aversion (Pflueger et al. (2020)), or frictions in credit markets. While we do not model real investment, it is also similar in spirit to Justiniano and Primiceri (2008)'s investment specific shock in the sense of driving a wedge between the intertemporal substitution in the real economy and the policy rate set by the central bank. It is also close to isomorphic to a shock to expected productivity growth (Beaudry and Portier (2006)), in the sense that a negative shock to expected growth similarly leads households to consume less at a given policy rate and drives consumption close to habit. Inflation in the model is determined from a log-linearized Phillips curve, which we micro-found through sticky wages in the manner of Rotemberg (1982), implying that we can equivalently define stocks as a levered claim to consumption or to firm profits.

We perform two main exercises. First, we calibrate the model to macroeconomic dynamics of long macroeconomic periods, and show that our model provides a reasonable link between macroeconomic changes of the 1980s vs. the 2000s and Treasury bond markets. We choose our break date to be 2001.Q2 following Campbell et al. (2020) when the correlation between inflation and the output gap turned from negative to positive (i.e., "stagflations"). This exercise shows that if we calibrate the shock volatilities and monetary policy to macroeconomic impulse responses, we obtain volatile supply shocks and monetary policy shocks but almost no demand shocks for the 1980s. Because during this period the policy rate responds fairly swiftly to inflation surprises in the data, we calibrate a monetary policy rule with little inertia. Partially adaptive inflation expectations generate predictability in inflation forecast errors in surveys, in line with the empirical evidence of Coibion and Gorodnichenko (2015), and reconcile volatile nominal Treasury bond yields with much less volatile long-term survey inflation expectations.

Even though the betas of nominal and real bond betas are not explicitly targeted in the calibration, the model generates a highly positive nominal bond–stock beta and a small but positive real bond–stock beta for the 1980s. The channel is simple: a positive Phillips curve or supply shock drives up inflation and inflation expectations, leading to lower nominal bond prices. Because monetary policy seeks to counteract this increase in inflation real rates also rise, and prices of real bonds fall, though the change is much smaller than for nominal bonds.

risks into these fundamental economic driving forces.

The higher real interest rates lead consumers to postpone consumption, and consumption falls toward habit, leading investors to put a lower valuation on risky stocks. The persistence and volatility of time-varying risk premia are not free parameters, but are disciplined by the empirical equity Sharpe ratio, the persistence of the equity price dividend ratio, and the predictability of equity returns from the lagged price-dividend ratio. Our model matches these equity market moments equally well as Campbell and Cochrane (1999) and Campbell et al. (2020).

The 1980s calibration of the model also generates strong bond return predictability from the yield spread, consistent with the corresponding empirical moment. A strong backward-looking component in the Phillips curve gives rise to a persistent inflation process, so under the expectations hypothesis long-term and short-term nominal rates are expected to respond similarly to a supply shock. Because risk premia in the model increase as consumption falls toward habit, a supply shock drives up the model yield spread through risk premia, and a positive yield spread predicts model bond excess returns positively. We therefore show that a strongly backward-looking Phillips curve, which has been found necessary to explain several features in macroeconomic data (Fuhrer (1997)), is also necessary to explain the empirical predictability of bond excess returns.

For the 2000s calibration of the model, we match the positive output gap–inflation and positive output gap–policy rate relationships in the data with highly volatile demand shocks, moderately volatile monetary policy shocks, and much smaller supply shocks. A more inertial monetary policy rule is consistent with a delayed empirical policy rate response to inflation surprises during this sample period. For the 2000s calibration we set inflation expectations to be rational and perfectly forward-looking, in line with a lack of predictability of survey inflation forecast errors during this period. While our model of monetary policy is purely descriptive and cannot speak to why the monetary policy rule has changed over time, the estimates seem intuitively in line with the gradual monetary policy rule of recent decades.

Even though the 2000s nominal and real bond betas were not targeted in the calibration stage, their broad features are well-matched by the model. The 2000s calibration generates negative stock market betas for both nominal and real bonds. The key channel depends on demand shocks, which tend to raise interest rates and inflation just as the output gap rises, and a gradual monetary policy response, which mutes and even reverses the output gap response to supply shocks. While the model counterfactually implies that nominal and real bond betas should have been the same during the 2000s, whereas in the data the nominal bond beta was more negative, we do not see this as a significant issue because the demand shock volatility is estimated with substantial noise from macroeconomic data. For the 2000s calibration, the model generates no return predictability in bonds, but strong return predictability in stocks, both of which are in line with the empirical evidence.

Our second exercise uses the calibrated model to conduct counterfactual exercises, asking what changes in shocks could turn nominal Treasury bonds similarly risky as during the stagflationary 1980s. The main finding is that positive nominal Treasury bond betas result from the interaction of volatile supply shocks with a non-inertial monetary policy rule. We show that if the model economy starts from the 2001.Q1–2019.Q4 calibration, several changes are needed to make nominal Treasury bond–stock betas positive. In particular, we find that increasing the volatility of supply shocks is not sufficient, but that both volatile supply shocks and a non-inertial monetary policy rule are needed. On the contrary, changing only the model shock volatilities back to their 1980s values leads to positive real bond betas and negative nominal bond betas in the model, in line with the empirical evidence toward the end of the sample in Figure 1. Asset pricing moments from Treasury markets therefore support the view that supply shocks matter for the real economy because monetary policy responds to these shocks (Bernanke et al. (1997)). This model finding also lines up well with our initial observation that while the recent post-pandemic shocks bear some resemblance to the supply shocks of the 1980s, the risks of nominal Treasury bonds in the data remain very different from the 1980s.

This research contributes to the broad literatures linking monetary policy and asset prices, understanding the sources of stagflations, and the drivers of changes in bond–stock comovements. The traditional view that monetary policy has short- to medium-term economic effects makes it appealing to use a model of financial market discounts that also respond to shorter-term fluctuations. Consumption habits in this paper are a prominent asset pricing model with this feature, but their integration with New Keynesian models with supply and demand shocks has been challenging.[3] Several prior papers have documented the changing risks in Treasury bonds and studied their drivers (e.g. Baele et al. (2010), Viceira (2012), David and Veronesi (2013), Campbell et al. (2017)), but the link between demand and supply shocks and Treasury bond betas has remained elusive. While some studies have focused on nominal bonds (Piazzesi and Schneider (2006), Song (2017), Campbell et al. (2020)) and others on real bonds (Chernov et al. (2021)), we show that the combination is informative about changes in the economy.

We also contribute to the long literature seeking to explain the extraordinary inflation dynamics in the 1980s. This literature can broadly be divided into a strand emphasizing

[3]Some research, including Uhlig (2007), Dew-Becker (2014), Rudebusch and Swanson (2008), Stavrakeva and Tang (2019), and Bretscher et al. (2020), has embedded simplified finance habit preferences into New Keynesian models. In contrast to them, we preserve the full nonlinearity of preferences that Campbell and Cochrane (1999) and Campbell et al. (2020) find important to simultaneously account for volatile equity risk premia and smooth risk-free rates in the data.

changes in shocks (Stock and Watson (2002), Sims and Zha (2006), Justiniano and Primiceri (2008)) and a strand emphasizing changes monetary policy (Clarida et al. (2000), Lubik and Schorfheide (2004), Bernanke et al. (1997)). One narrative that has emerged from this literature is that supply shocks were initially not recognized by monetary policy, forcing the Fed to raise interest rates drastically under Volcker, which resulted in severe stagflation (Primiceri (2006)). We contribute by bringing new asset pricing moments to this literature in order to speak to the question of shocks vs. policy. We show that these new moments support a narrative whereby the interaction of supply shocks and monetary policy was essential to generate the risky nominal Treasury bond markets of the stagflationary 1980s, and would be needed to turn Treasury markets back into a similar regime.

We view this research as complementary to recent work by Bianchi et al. (2022a), Bianchi et al. (2022b), Gourio and Ngo (2020), and Li et al. (2022), who model changing Treasury bond risks within New Keynesian models of monetary policy, but in contrast to us assume constant volatilities of fundamental shocks and CRRA or recursive preferences with constant risk aversion. By contrast, we focus on the interaction between monetary policy and the volatilities of fundamental shocks, as well as the predictability of Treasury bond excess returns from endogenously time-varying risk premia. Our contribution is also complementary to the more reduced-form approach of Chernov et al. (2021), who use rolling correlations rather than betas to argue that the time-varying bond–stock comovements are similar for inflation-indexed and nominal bonds. However, if the same structural shock drives both real bond yields and inflation expectations, as in most New Keynesian models, a correlation measure may be uninformative about their separate economic roles. Our focus on betas reveals distinct differences between nominal and real bond risks pre-2000, which we attribute to demand and supply shocks, and their interaction with monetary policy.

The rest of the paper proceeds as follows. We present the model in Section 2. We estimate macroeconomic impulse responses and inflation forecast error regressions by subperiod and describe our calibration strategy in Section 3. Section 4 describes the model's fit for macroeconomic and asset pricing moments for the 1980s and 2000s subperiods. Section 5 presents the counterfactual exercises. Finally, Section 6 concludes.

2 Model

The model combines a small-scale log-linearized New Keynesian model on the macroeconomic side with a model of habit-formation preferences for asset prices, following Campbell and Cochrane (1999) and Campbell et al. (2020). Different from Campbell et al. (2020) the model features a monetary policy rule and monetary policy shocks, and different from Pflueger and

Rinaldi (2022) it features supply and demand shocks.[4] We use lower-case letters to denote logs, π_t to denote log price inflation, and π_t^w to denote log wage inflation. We refer to price inflation and inflation interchangeably.

2.1 Preferences

As in Campbell et al. (2020) and Pflueger and Rinaldi (2022), 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. 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:

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

As equation (2) makes clear, a model for market habit implies a model for surplus consumption and vice versa. Market consumption habit is modeled implicitly by assuming that log surplus consumption, s_t, satisfies:

$$s_{t+1} = (1-\theta_0)\bar{s} + \theta_0 s_t + \theta_1 x_t + \theta_2 x_{t-1} + \lambda(s_t)\varepsilon_{c,t+1}, \tag{3}$$

$$\varepsilon_{c,t+1} = c_{t+1} - \mathrm{E}_t c_{t+1}. \tag{4}$$

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

$$\lambda(s_t) = \begin{cases} \frac{1}{\bar{S}}\sqrt{1-2(s_t-\bar{s})} - 1 & s_t \leq s_{max} \\ 0 & s_t > s_{max} \end{cases}, \tag{5}$$

$$\bar{S} = \sigma_c \sqrt{\frac{\gamma}{1-\theta_0}}, \tag{6}$$

$$\bar{s} = \log(\bar{S}), \tag{7}$$

$$s_{max} = \bar{s} + 0.5(1-\bar{S}^2). \tag{8}$$

[4] An earlier working paper version of Campbell et al. (2020) had a small-scale New Keynesian macroeconomic model, though it did not feature demand shocks to the Euler equation, and instead suffered from an over-reliance on shocks to the central bank inflation target. This earlier working paper version also did not match macroeconomic impulse responses as we do.

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, which in equilibrium is conditionally homoskedastic and lognormal. As shown in Campbell et al. (2020), the specification for log surplus consumption (3) implies that log market habit follows approximately a weighted average of moments of past log consumption.

Here, x_t equals stochastically detrended consumption (up to a constant):

$$x_t = c_t - a_t, \tag{9}$$

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

where ϕ is a smoothing parameter. For the microfoundations presented in the Appendix, consumption equals output and x_t equals the log output gap, or the difference between between log output and log potential output under flexible prices and wages, a_t. For details, see the Appendix.

2.2 Macroeconomic Euler Equation and Demand Shocks

Different from Campbell et al. (2020) and Pflueger and Rinaldi (2022) and new to this paper, we introduce a preference shock for bonds that gives rise to a demand shock in the macroeconomic dynamics for consumption and output. The stochastic discount factor (SDF) M_{t+1} in this economy equals:

$$M_{t+1} = \beta\frac{\frac{\partial U_{t+1}}{\partial C}}{\frac{\partial U_t}{\partial C}} = \beta\exp\left(-\gamma(\Delta s_{t+1} + \Delta c_{t+1})\right). \tag{11}$$

We assume that investors have an i.i.d. preference shock for bonds, ξ_t, implying that the Euler equation for the one-period risk-free rate equals

$$1 = E_t\left[M_{t+1} exp\left(r_t - \xi_t\right)\right]. \tag{12}$$

For example, a 10 bps increase in ξ_t would mean that consumers increase their current consumption as if the real risk-free rate was lower by 10 bps than it actually is. Such an increase in ξ_t could represent a shock to the convenience of risk-free bonds or frictions in credit and banking markets, driving a wedge between market interest rates and consumers' borrowing and savings decisions. The preference shock ξ_t is assumed to be conditionally homoskedastic, serially uncorrelated, and uncorrelated with other shocks.

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

$$r_t = \gamma \mathrm{E}_t \Delta c_{t+1} + \gamma \mathrm{E}_t \Delta s_{t+1} - \frac{\gamma^2}{2} \left(1+\lambda(s_t)\right)^2 \sigma_c^2 + \xi_t, \tag{13}$$

$$= \gamma \mathrm{E}_t \Delta c_{t+1} + \gamma \theta_1 x_t + \gamma \theta_2 x_{t-1} + \underbrace{\gamma(\theta_0 - 1) s_t - \frac{\gamma^2}{2} \left(1+\lambda(s_t)\right)^2 \sigma_c^2}_{=0} + \xi_t. \tag{14}$$

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

$$x_t = f^x E_t x_{t+1} + \rho^x x_{t-1} - \psi r_t + v_{x,t}. \tag{15}$$

Imposing the restriction that the forward- and backward-looking terms in the Euler equation add up to one, we get that the Euler equation parameters equal

$$\rho^x = \frac{\theta_2}{\phi - \theta_1}, f^x = \frac{1}{\phi - \theta_1}, \psi = \frac{1}{\gamma(\phi - \theta_1)}, \theta_2 = \phi - 1 - \theta_1. \tag{16}$$

Pflueger and Rinaldi (2022) show that non-zero values for the habit parameters, θ_1 and θ_2, generate a New Keynesian block with forward- and backward-looking coefficients, which is needed to match the hump-shaped output impulse response to a monetary policy shock in the data. The new demand shock in the Euler equation equals

$$v_{x,t} = \psi \xi_t. \tag{17}$$

The demand shock $v_{x,t}$ is conditional homoskedastic, serially uncorrelated and uncorrelated with supply and monetary policy shocks because ξ_t is. The standard deviation of $v_{x,t}$ is denoted by σ_x.

2.3 Phillips Curve and Supply Shocks

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

$$\pi_t^w = f^\pi E_t \pi_{t+1}^w + \rho^\pi \pi_{t-1}^w + \kappa x_t + v_{\pi,t}, \tag{18}$$

for constants ρ^π, f^π, and κ. The supply or Phillips curve shock $v_{\pi,t}$ is assumed to be conditionally homoskedastic with standard deviation $\sigma_{\pi,t}$, serially uncorrelated, and uncorrelated with other shocks. This supply shock can arise from a variety of sources, such as variation in optimal wage markups charged by unions or shocks to the marginal utility of leisure.[5]

In deriving the Phillips curve (18), we allow for adaptive subjective inflation expectations of the form

$$\tilde{E}_t \pi^w_{t+1} = (1-\zeta) E_t \pi^w_{t+1} + \zeta \pi^w_{t-1}, \tag{19}$$

where E_t denotes the rational expectation conditional on state variables at the end of period t. The case $\zeta = 0$ corresponds to rational forward-looking inflation expectations, while $\zeta > 0$ reflects partially adaptive and backward-looking inflation expectations. A long-standing Phillips curve literature has found that adaptive inflation expectations and a strongly backward-looking Phillips curve are helpful for capturing the empirical persistence of inflation (Fuhrer and Moore (1995), Fuhrer (1997)).[6] We add to this literature by showing that partially adaptive inflation expectations are also necessary to explain the empirical bond return predictability initially documented by Fama and Bliss (1987) and Campbell and Shiller (1991), and ask how adaptive inflation expectations affect bond–stock betas. If $\rho^{\pi,0}$ is the backward-looking component obtained under rational inflation expectations ($\zeta = 0$) because wage-setters index their wages to past inflation, the backward-looking Phillips curve parameter with hybrid inflation expectations equals

$$\rho^\pi = \rho^{\pi,0} + \zeta - \rho^{\pi,0}\zeta. \tag{20}$$

The backward- and forward-looking Phillips curve parameters add up to one:

$$f^\pi = 1 - \rho^\pi. \tag{21}$$

Assuming sticky wages rather than sticky prices allows us to marry the traditional view of equities as a levered claim on consumption from the consumption-based literature (Abel (1990)) with the definition of stocks as a levered claim on real firm profits, since these definitions are equivalent in our model. This distinction is inconsequential for the macroeconomic dynamics of the output gap, inflation, and interest rates in our model, but it matters for the cyclicality of firm profits and hence for asset prices. This is in line with Christiano et al. (1999) who find that sticky wages are much more important for aggregate inflation dynamics

[5] Up to the distinction between wage and price inflation, Phillips curve shocks would also be isomorphic to shifts to potential output that are unrecognized by the central bank and consumers, in which case $x_t + \frac{1}{\kappa} v_{\pi,t}$ would need to be interpreted as the actual the output gap and x_t as the output gap perceived by consumers and the central bank.

[6] Consistent with this older literature that emphasized aggregate inflation dynamics, a quickly growing literature has documented deviations from rationality (Coibion and Gorodnichenko (2015), Bianchi et al. (2022a)) and excess dependence on lagged inflation (Malmendier and Nagel (2016)).

than sticky prices. It is also in line with Favilukis and Lin (2016) who find that wage-setting frictions are important to capture pro-cyclical firm profits and ensure that a claim to firm profits behaves similarly to a claim to consumption in an asset pricing sense. Our microfoundations with flexible prices and sticky wages are particularly appealing because they imply that real firm profits are proportional to real output and hence real consumption, and therefore a claim to consumption is identical to a claim to firm profits.

In the Appendix we present a simple set of microfoundations for the log-linearized wage Phillips curve (18). We consider the simplified case with flexible product prices but sticky wages. Specifically, we assume that wage-setters face a quadratic cost as in Rotemberg (1982) if they raise wages faster than past inflation. The indexing to past inflation is analogous to the indexing assumption in Smets and Wouters (2007) and Christiano et al. (2005). The Phillips curve describing the wage inflation dynamics arises from log-linearizing the intratemporal first-order condition of wage-setting unions. The parameter κ is a wage-flexibility parameter. Because prices are flexible, price inflation equals wage inflation minus productivity growth:

$$\pi_t \;=\; \pi_t^w - \Delta a_t \;=\; \pi_t^w - (1-\phi)x_t. \tag{22}$$

In our calibrations, price and wage inflation are very similar and the gap between them is small.

In order to present the simplest possible model of monetary policy and finance habits we do not explicitly model real investment. The aggregate resource constraint therefore simply states that aggregate consumption equals aggregate output:

$$C_t = Y_t. \tag{23}$$

2.4 Monetary Policy

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):

$$i_t \;=\; \rho^i i_{t-1} + \left(1-\rho^i\right)\left(\gamma^x x_t + \gamma^\pi \pi_t\right) + v_{i,t}, \tag{24}$$

$$v_t \;\sim\; N\left(0, \sigma_i^2\right). \tag{25}$$

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, $v_{i,t}$, 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 the rule. The policy rate then mean-reverts slowly at rate ρ^i. To keep the solution for macroeconomic dynamics log-linear, we use the common log-linear approximation to the real risk-free rate[7] $r_t = i_t - E_t\pi_{t+1}$.

2.5 Asset Prices

Investors price bonds and stocks with the stochastic discount factor given by (11), and the preference or Treasury convenience shock ξ_t that enters into the asset pricing equations for bonds but not for stocks. We assume that wage-setters have adaptive expectations (19) but that asset prices are formed with rational expectations, capturing the idea that markets are more sophisticated and more attentive to macroeconomic dynamics than individual wage-setters. A similar assumption has been used by Bianchi et al. (2022a). Bond prices are given by the recursions:

$$P_{1,t}^{\$} = exp(-i_t),\ P_{1,t} = exp(-r_t), \tag{26}$$

$$P_{n,t}^{\$} = exp(-\xi_t)E_t\left[M_{t+1}exp(-\pi_{t+1})P_{n-1,t+1}^{\$}\right],\ P_{n,t} = exp(-\xi_t)E_t\left[M_{t+1}P_{n-1,t+1}\right], \tag{27}$$

where one-period real and nominal interest rates are given by equation (12) and the Fisher equation

$$i_t = E_t\pi_{t+1} + r_t. \tag{28}$$

The latter equation is an approximation, effectively assuming that the inflation risk premium in one-period nominal bonds is zero. The assumption that all bonds are priced with the preference shock ξ_t ensures that in the absence of uncertainty the expectations hypothesis holds for nominal and real bonds.

Because consumption claims do not benefit from the preference or Treasury convenience shock, the asset pricing recursion for consumption claims takes the following form

$$\frac{P_{n,t}^c}{C_t} = E_t\left[M_{t+1}\frac{C_{t+1}}{C_t}\frac{P_{n-1,t+1}^c}{C_{t+1}}\right]. \tag{29}$$

[7]We do not model the zero lower bound here, because we are interested in longer-term regimes, and a substantial portion of the zero lower bound period appears to have been governed by expectations of a swift return to normal (Swanson and Williams (2014)). The zero-lower-bound may however be important for more cyclical changes in bond–stock betas, as emphasized by Gourio and Ngo (2020), and we leave this to future research.

The price-consumption ratio for a claim to all future consumption then equals

$$\frac{P_t^c}{C_t} = \sum_{n=1}^{\infty} \frac{P_{n,t}}{C_t}. \tag{30}$$

We model stocks as a levered claim on consumption or equivalently firm profits, while preserving the cointegration of consumption and dividends as in Campbell et al. (2020). 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 $(1-\delta)P_t^c$. The price of the levered equity claim equals $P_t^\delta = \delta P_t^c$. Leverage hence scales stock returns roughly proportionally, increasing stock return volatility but leaving the Sharpe ratio unchanged.

We model the demand shock as arising from a preference shock for bonds rather than from a shock to the discount factor β shared by bonds and stocks (Albuquerque et al. (2016)), because a shock to the discount factor β would generally drive down both bonds and stocks at the same time and generate strongly positive bond–stock correlations, in stark contrast to the post-2001 data. Our preference shock ξ_t, by contrast, drives down only the price of bonds, while stock prices respond according to the general equilibrium changes in expected consumption and the stochastic discount factor M_{t+1}. However, our preference shock ξ_t shares the feature of the valuation shocks of Albuquerque et al. (2016) of driving a wedge between consumption news and interest rates, thereby capturing an important feature in the data (Duffee (2022)).

2.6 Model Solution

The solution proceeds in two steps. First, we solve for log-linear macroeconomic dynamics. Second, we use numerical methods to solve for highly non-linear asset prices. This is aided by the particular tractability of Campbell et al. (2020)'s preferences, which imply that the surplus consumption ratio is a state variable for asset prices but not for macroeconomic dynamics. We solve for the dynamics of the log-linear state vector

$$Y_t = [x_t, \pi_t^w, i_t]'. \tag{31}$$

Equilibrium macroeconomic dynamics are determined by the consumption Euler equation (15), the Phillips curve (18), and the monetary policy rule (24). We solve for a minimum state variable equilibrium of the form

$$Y_t = BY_{t-1} + \Sigma v_t, \tag{32}$$

$$v_t = [v_{x,t}, v_{\pi,t}, v_{i,t}], \tag{33}$$

where B and Σ are $[3 \times 3]$ and $[3 \times 3]$ matrices, and v_t is the vector of structural shocks. We solve for the matrix B using Uhlig (1999)'s formulation of the Blanchard and Kahn (1980) method. We then solve for equilibrium consumption dynamics by inverting the relationship (10). In both our calibrations, there exists a unique equilibrium of the form (32) with non-explosive eigenvalues. We acknowledge that, 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 the scope of this paper. Note that equation (32) implies that macroeconomic dynamics are conditionally lognormal. The output gap–consumption link (10) therefore implies that equilibrium consumption surprises $\varepsilon_{c,t+1}$ are conditionally lognormal, as previously conjectured.

The solution for asset prices uses the numerical value function iteration algorithm of Campbell et al. (2020) to implement asset pricing recursions (26) through (30) while accounting for the new demand shock and the link between wage and price inflation (22). As a result of the new demand shock asset prices have five state variables: the three state variables included in Y_t, the lagged output gap x_{t-1}, and the surplus consumption ratio s_t. We need x_{t-1} as an additional state variable because the expected surplus consumption ratio depends on it through the dynamics (3). In the absence of demand shocks the lagged output gap does not enter as a separate state variable because x_{t-1} can be expressed as a linear combination of the time-t state vector Y_t. This is no longer possible in the presence of the new demand shock in this paper, thereby adding x_{t-1} as a new state variable for asset prices relative to Campbell et al. (2020).

3 Empirical Analysis and Calibration Strategy

3.1 Calibration Strategy

Because we are interested in economic changes over time, we calibrate the model separately for two subperiods, where we choose the 2001.Q2 break date from Campbell et al. (2020). Importantly, this break date was chosen by testing for a break date in the inflation–output gap relationship, and did not use asset prices. We start our sample in 1979.Q4, when Paul Volcker was appointed to be Fed chairman. We end our sample in 2019.Q4 prior to the pandemic, leaving the analysis of how shocks changed during the pandemic period for a separate discussion at the end of the paper. However, because the pandemic period represents a small portion of our sample, little would change if we folded it into our post-2001.Q2 sample period. We do not account for the possibility that agents might have anticipated a change in regime.[8]

Our calibration procedure proceeds in three steps. First, we set some parameters to values following the literature. Those parameter values are held constant across both subperiods and are shown in the top panel of Table 1. The expected consumption growth rate, utility curvature, the risk-free rate, and the persistence of the surplus consumption ratio (θ_0) are from Campbell and Cochrane (1999), who found that a utility curvature of $\gamma = 2$ gives an empirically reasonable equity Sharpe ratio and set θ_0 to match the quarterly persistence of the equity price-dividend ratio in the data. The output gap–consumption link parameter $\phi = 0.99$ is chosen similarly to Campbell et al. (2020) to maximize the empirical correlation between stochastically detrended real GDP and the output gap from the Bureau of Economic Analysis. We choose a somewhat higher value compared to Campbell et al. (2020) because the correlation between the output gap and stochastically de-trended real GDP is basically flat over a range of values ($correlation = 76\%$ at $\phi = 0.93$ vs. $correlation = 73\%$ at $\phi = 0.99$), but a larger value for ϕ minimizes the gap between price and wage inflation and therefore simplifies the model by circumventing the need to model sticky prices separately from sticky wages. We set θ_1 so that $\theta_1 - \phi$ and hence the Euler equation are exactly as in Pflueger and Rinaldi (2022), where the habit parameters θ_1 and θ_2 were chosen to replicate the hump-shaped response of output to an identified monetary policy shock in the data. Because the model impulse responses to a monetary policy shock are invariant to the shock volatilities, and vary little with monetary policy rule and Phillips curve parameters, we therefore effectively match θ_1 to the output response to an identified monetary policy shock in the data. The second habit parameter, θ_2 is implied and set to ensure that the backward- and forward-looking components in the Euler equation sum up to one. In addition to those consumption and preference parameters, we set the slope of the Phillips curve to a value from the literature. Specifically, the Phillips curve slope is set to $\kappa = 0.0062$ as recently estimated from cross-regional inflation and output data in Hazell et al. (2022), who also find little variation in this parameter over time periods.

In a second step, we choose subperiod-specific monetary policy parameters γ^x, γ^π, and ρ^i and shock volatilities σ_x, σ_π, and σ_i to match the macroeconomic impulse responses and volatilities, while holding the inflation expectations parameter constant at $\zeta = 0$. We target

[8] Cogley and Sargent (2008) have shown that an approximation with constant transition probabilities often provides a good approximation of fully Bayesian decision rules.

macroeconomic lead-lag moments that are intuitively informative about the combination of demand, supply, and monetary policy shocks and the monetary policy rule. In addition, we match the macroeconomic volatilities of the output gap, inflation expectations, and the policy rate. Formally, we choose the monetary policy parameters (γ^x, γ^π, ρ^i) and shock volatilities (σ_x, σ_π, σ_i) to minimize an objective function that equals a weighted sum of squared distances between model and data moments. Our objective function includes the standard deviation of annual real consumption growth, the annual change in the federal funds rate, and the annual change in survey ten-year inflation expectations.[9] To match macroeconomic lead-lag relationships, the objective function also includes the empirical impulse responses depicted in Figure 2. We include the output gap response to price inflation innovations, the output gap response to fed funds rate innovations, and the fed funds rate response to price inflation innovations, all at one, three, and seven quarter forecast horizons. For the 2000s period when wage inflation data is available, we also include the difference between the output gap responses to contemporaneous price inflation and the output gap response to contemporaneous wage inflation. We include only one moment for wage inflation because we want to avoid over-weighting inflation moments by including many nearly identical moments. The estimation of empirical impulse responses is described in detail in Section 3.2. Our objective function then equals the sum of squared z-scores measuring the gap between simulated model and data moments, with empirical standard deviations computed via the delta method for the standard deviations of macroeconomic annual changes and with Newey–West standard errors with h lags for impulse responses.[10]

In a third step, we choose the adaptive inflation expectations parameter ζ to match the empirical evidence on Campbell and Shiller (1991) return predictability regressions in the data for each subperiod, while holding all other parameters constant at their values chosen in the second step. We use a separate step because the computation of asset prices is substantially slower than the computation of of macroeconomic dynamics. This separate step also allows the algorithm to put special weight on this asset pricing moment and transparently links this moment to the adaptive inflation expectations parameter ζ.

[9] Empirical ten-year CPI inflation expectations are from the Survey of Professional Forecasters after 1990 and from Blue Chip before that. Long-term inflation forecasts are available from the Philadelphia Fed research website. Model ten-year inflation expectations are computed assuming that inflation expectations are adaptive, i.e., $\tilde{E}_t \pi_{t\to t+40} = \zeta \pi_{t-41\to t-1} + (1-\zeta) E_t \pi_{t\to t+40}$, where E_t denotes rational expectations.

[10] Our grid search procedure is relatively simple and draws 50 random values for (γ^x, γ^π, ρ^i) and (σ_x, σ_π, σ_i) and picks the combination with the lowest objective function for each subperiod calibration. We verify that the algorithm has converged by checking that the same parameter values are obtained when we re-run the code with new random draws. We also verify that this algorithm has sufficient precision to clearly reject the parameter values for the 1980s calibration against the 2000s data and vice versa. The only parameter value that reaches our externally set upper bound is $\gamma^x = 2$ for the 2000s calibration. We regard this as a plausible upper bound based on economic priors.

It is well-known that the term spread, or the difference between long- and short-term bond yields, predicts excess returns on long-term bonds. This leads us to set $\zeta = 0.6$ for the 1979.Q4–2001.Q1 subperiod and $\zeta = 0$ for the 2001.Q2–2019.Q4 subperiod. For the first subperiod we choose $\zeta = 0.6$ because the Campbell–Shiller regression coefficient appears to have converged and barely changes as we increase ζ further. The resulting implied Phillips curve coefficient equals $\rho^{\pi} = 0.8$, consistent with Fuhrer (1997)'s estimation based on the empirical properties of inflation. For the more recent 2001.Q2–2019.Q4 subperiod, we set $\zeta = 0$ while acknowledging that this parameter is poorly identified for this subperiod of extremely stable inflation. While the distance between the model and data Campbell–Shiller regression coefficients is minimized at $\zeta = 0$ for the 2001.Q2–2019.Q4 calibration, this distance is relatively flat with respect to ζ, leaving ζ poorly identified. We discuss in our counterfactual analysis in Section 5 how model implications change when inflation expectations in 2001.Q2–2019.Q4 are instead assumed to be adaptive similarly to the 1979.Q4–2001.Q1 calibration. Finally, the leverage parameter is chosen to roughly match the volatility of equity returns. Notably, we do not need a high leverage parameter, with $\delta = 0.5$ for the 1980s calibration corresponding to a leverage ratio of 50%, and $\delta = 0.66$ for the 2000s calibration corresponding to a leverage ratio of 33%.

3.2 Macroeconomic Impulse Responses

What changed in the economy from the earlier subperiod with positive nominal bond–stock betas to the more recent subperiod with negative nominal bond–stock betas? Before turning to the model and asset prices, we use simple reduced-form analyses of macroececonomic data. We are interested in four dynamic cross-correlations: output gap–inflation, output gap–wage inflation, output gap–policy rate, and policy rate–inflation. We estimate Jordà (2005)-type impulse responses and visualize them in Figure 2. Output gap impulse responses to inflation and interest surprises are included because they are intuitively informative about the presence of demand, supply, and monetary policy shocks in the tradition of the lead-lag relationships estimated by Fuhrer (1997), Galı and Gertler (1999), and others. For the 2000s subperiod, when wage index data is easily available, we also separately show the output gap impulse responses to wage and price inflation surprises, thereby showing that the model-implied link between prices and wages is reasonable. Finally, the empirical impulse response of the fed funds rate to an inflation surprise intuitively captures information about the nature of the monetary policy rule in the tradition of Taylor (1993).[11]

[11] We put inflation and the policy rate on the right-hand side of our empirical impulse responses because the resulting impulse responses are less sensitive to noise in the output gap. On the other hand, if the true output gap moves smoothly but is occasionally mismeasured this could lead to substantial measurement

It is important to keep in mind that the empirical analysis in Figure 2 does not attempt to identify different structural shocks, but instead provides reduced-form lead-lag relationships. In this Section, we discuss how these reduced-form relationships should intuitively load onto different shocks and the monetary policy rule. The economically and statistically significant changes in the output, inflation, and interest rate lead-lag relationships documented in this Section, combined with the intuition that stocks comove positively with output, nominal bond prices comove negatively with inflation expectations and real rates, and real bond prices move negatively with real rates, strongly suggest that these macroeconomic changes should change the risks of nominal and real Treasury bonds. In Section 4, we will use these same empirical moments to fit structural parameters, and derive the model-implied nominal and real Treasury bond betas. Our initial empirical evidence is consistent with popular macroeconomic accounts and reaches a different conclusion than Duffee (2022) because we rely on realized output, inflation, and interest rates rather than innovations to surveys, which may be subject to underreaction to news (Coibion and Gorodnichenko (2015)).[12]

Figure 2, Panel A, shows the output gap–inflation relationship for our two subperiods. The corresponding model relationships are also included in the plots. Panel A plots the forecast horizon h in quarters on the x-axis against the coefficient $a_{1,h}$ on the y-axis:

$$x_{t+h} = a_{0,h} + a_{1,h}\pi_t + a_{2,h}\pi_{t-1} + \varepsilon_{t+h}. \tag{34}$$

The left plot in Panel A shows the results from estimating (34) for the 1980s subperiod, while the right plot shows the analogous results for the 2000s subperiod. Panel B estimates analogous impulse response functions using wage inflation (ECIWAG, available starting in 2000 from the St. Louis Fred), though only for the 2000s subperiod. The impulse responses in Panels A and B paint an intuitive picture of the dominance of supply vs. non-supply (i.e., demand and monetary policy) shocks in the economy. When supply shocks in the Phillips curve (18) are dominant, inflation surprises should be associated with declines in the output gap. This is exactly the empirical pattern we see in the left plot in Panel A for the earlier subperiod 1979.Q4–2001.Q1, giving a first empirical indication that this was a period driven by supply shocks to the Phillips curve. By contrast, the right plots in Panels A and B show that positive inflation surprises during the 2001.Q2–2019.Q4 period tended to be followed

error for impulse responses that put the output gap on the right-hand side.

[12] We also take a more structural view of stocks being linked to output and bonds being linked to nominal and real interest rates, rather than allowing for flexible loadings of bonds and stocks onto all macroeconomic factors as in Duffee (2022). While a full analysis of the differences between realized and survey-based inflation–output covariances is beyond the scope of this paper, we find that incorporating time-varying risk premia through habit formation preferences and partially backward-looking inflation expectations can account not only for inflation forecast error predictability, but also for bond excess return predictability, and relatively low volatility of ten-year survey inflation expectations.

by increases in the output gap, as we would expect if demand and monetary policy shocks move inflation and the output gap along a stable Phillips curve. The empirical output gap-wage inflation relationship is slightly more positive than the relationship with price inflation, consistent with a higher output gap being associated with an increase in productivity, as in our model.

While the empirical output gap–inflation lead-lag relationships in Panel A are indicative of a change from large supply shocks to smaller supply shocks during the 2000s, they are not informative about the distinction between monetary policy and demand shocks. We therefore turn to the relationship between the output gap and the policy rate, which we estimate through the following regression:

$$x_{t+h} = a_{0,h} + a_{1,h} i_t + a_{2,h} i_{t-1} + \varepsilon_{t+h}. \tag{35}$$

If the economy is driven by monetary policy shocks, we would expect an increase in the policy rate to be followed by a hump-shaped decline in the output gap, as estimated in a large literature estimating how identified monetary policy shocks affect output and consumption (see Ramey (2016) for a survey). Conversely, when demand shocks are present, we would expect this pattern to be reversed, and increases in the output gap should go along with increases in the policy rate. Further, in the case with mostly demand shocks, the magnitude of the output gap–interest rate relationship should be closely related to the monetary policy output weight γ^x. The left figure in Panel C shows that during the earlier subperiod high interest rates were indeed followed by a lower output gap, suggesting that during this subperiod interest rate surprises reflected large monetary policy shocks. Conversely, the right plot of Panel C shows a positive relationship between interest rate innovations and the output gap, suggesting that this period was dominated by demand shocks. The right plot also shows that during the 2000s a one percentage point increase in the output gap was associated with a roughly one-half percentage point increase in the policy rate. A naive back-of-the envelope calculation therefore suggests that the immediate monetary policy response to the output gap, or the product $(1-\rho^i)\gamma^x$, was roughly ≈ 0.5 during the 2000s.

Finally, we estimate impulse responses of interest rates to inflation through the following regression:

$$i_{t+h} = a_{0,h} + a_{1,h} \pi_t + a_{2,h} \pi_{t-1} + \varepsilon_{t+h}. \tag{36}$$

These impulse responses are useful, because we would expect them to reflect the speed and strength of the monetary policy response to inflation. Panel D shows that interest rates showed a somewhat more than one for one response to an inflation surprise in both subperiods, though the interest rate response peaks earlier during the first subperiod. By contrast, during the second subperiod the interest rate response peaks later, as would be the case if the Federal Reserve followed a more inertial monetary policy rule.

Taken together, the macroeconomic impulse responses support an intuitive narrative of the broad economic changes from the 1979.Q4–2001.Q1 subperiod to the more recent 2001.Q2–2019.Q4 subperiod. The reduced-form empirical evidence from the macroeconomic data supports the notion that the 1979.Q4–2001.Q1 period was dominated by supply and monetary policy shocks, while the 2001.Q2–2019.Q4 period was dominated by demand shocks. It appears that monetary policy counteracted inflation fluctuations more than one for one in both subperiods, as required to satisfy the Taylor principle and avoid sunspots. However, while the monetary policy response was immediate in the Volcker subperiod, it was more gradual during the more recent period.

3.3 Predictability of Inflation Forecast Errors

To validate our calibration of the inflation expectations parameter, we run some simple reduced-form analysis testing for the rationality of inflation expectations by subperiod. Table 2 runs the well-known tests for the rationality of inflation expectations proposed by Coibion and Gorodnichenko (2015):

$$\pi_{t+4} - \tilde{E}_{t+1}\pi_{t+4} = a_0 + a_1 \left(\tilde{E}_{t+1}\pi_{t+4} - \tilde{E}_t \pi_{t+4} \right) + \varepsilon_{t+4}. \tag{37}$$

Here, a tilde denotes potentially subjective inflation expectations. If expectations are full information rational the forecast error on the left-hand side of (37) should be unpredictable, and the coefficient a_1 should equal zero. Our empirical specification follows Coibion and Gorodnichenko (2015) as closely as possible, using the Survey of Professional Forecasters four-quarter and three-quarter GDP deflator inflation forecasts to compute forecast revisions. The first column in Table 2 uses a long sample 1968.Q4-2001.Q1 and confirms their well-known empirical result. An upward revision in inflation forecasts tends to predict a positive forecast error. Said differently, realized inflation tends to come in even higher than the revised forecast, when the forecast has recently increased. This is generally interpreted as evidence that forecasters underreact to incoming information about inflation. The second and third columns run the same empirical regressions for our 1979.Q4–2001.Q1 and 2001.Q2–2019.Q4 subperiods. We find that for both subperiods the evidence becomes insignificant. While this is potentially due to the smaller sample size and weaker statistical power, the point estimate for the most recent subperiod even switches sign and becomes negative. When we formally test for the significance of the interaction with a time dummy, the difference between the 1968.Q4-2001.Q1 and 2001.Q2–2019.Q4 forecast revision coefficients is statistically significant. The reduced-form evidence is therefore consistent with the notion that inflation expectations during the 2001.Q2–2019.Q4 period were full information rational, in contrast to the empirical evidence from earlier decades.

The literature has not reached an agreement on whether inflation expectations have become more or less rational over time. On the one hand, Bianchi et al. (2022b) find less inflation forecast error predictability post-1995, and Davis (2012) shows that inflation expectations have become less responsive to oil prices shocks in recent decades. However, Coibion and Gorodnichenko (2015) and Maćkowiak and Wiederholt (2015) provide evidence and a model of decreasing attention to inflation as economic volatility declined during the 1990s. Because the inflation expectations formation process is fundamentally hard to estimate when inflation is low and stable, it will therefore be important to check how results for the 2001.Q2–2019.Q4 calibration change when the expectations parameter ζ takes different values.

4 Model Results for the Macroeconomy and Asset Prices

We first verify that the model captures the macroeconomic changes from the first subperiod to the second subperiod in the data. We then turn to the asset pricing properties, and show that the model replicates both the unconditional and subperiod-specific return predictability in stocks and bonds. The model also generates strongly positive nominal bond–stock betas and weakly positive real bond–stock betas in the 1979.Q4–2001.Q1 subperiod calibration, and negative nominal and real bond–stock betas in the 2001.Q2-2019.4 subperiod. This fit for bond-stock betas is achieved even though we did not target them directly in the calibration procedure, which only used macroeconomic moments and the predictability of bond returns.

4.1 Structural Macroeconomic Impulse Responses

Figure 3 illustrates the model mechanism by showing model impulse responses of our macroeconomic state vector to one-standard-deviation structural shocks for both calibrations. The 1979.Q4–2001.Q1 calibration is shown with black solid lines, while the 2001.Q2–2019.Q4 calibration is shown with red dashed lines. The first column shows a one-standard-deviation demand shock, the second column shows a one-standard-deviation supply shock, and the third column shows a one-standard-deviation monetary policy shock. The rows show the output gap (in %), nominal policy rate (in annualized %), and wage inflation rate (in annualized %). The impulse responses to a monetary policy shock are almost identical to those analyzed in Pflueger and Rinaldi (2022), who showed that by matching the empirical evidence for the output response to monetary policy shocks it is also possible to explain the high-frequency response of the stock market to monetary policy surprises around FOMC announcements. The impulse responses to demand shocks are also intuitive. For the earlier subperiod calibration demand shocks are essentially zero, and so there are no meaningful impulse responses. But in the 2001.Q2–2019.Q4 subperiod calibration we see that a demand shock leads to an immediate increase in the output gap and an increase in the policy rate, while having only a small but positive effect on inflation.

Finally, the Phillips curve shock has impulse responses that differ meaningfully across the two subperiod calibrations. For the 1979.Q4–2001.Q1 calibration a positive Phillips curve shock leads to an immediate and persistent jump in inflation, a rapid increase in the policy rate, and a gradual but large and persistent decline in the output gap. By contrast, for the 2001.Q2–2019.Q4 calibration, a Phillips curve shock leads to a more short-lived increase in inflation, a significantly more gradual increase in the policy rate, and almost no change in the output gap. For this calibration, a monetary policy rule that prescribes very little immediate tightening in response to such a shock means that the real rate initially falls, and the output gap barely declines and initially may even increase in response to a Phillips curve shock. The inflation increase in the 2001.Q2–2019.Q4 calibration is also less persistent due to the forward-looking inflation expectations ($\zeta = 0$). Hence, these impulse responses show that even if supply shocks had been very volatile during the 2001.Q2–2019.Q4 period, their effect on the macroeconomy would likely have been very different and they would likely not have led to stagflation, unlike the case in the 1980s.

4.2 Macroeconomic Dynamics in the Model and in the Data

Figure 2 shows the results of estimating analogous impulse response regressions in the model as in the data, and the bottom panel of Table 3 compares macroeconomic volatilities. For the 1979.Q4–2001.Q1 subperiod, the model matches the deline in the output gap in response to an inflation innovation, the decline in the output gap in response to a policy rate innovation, and the lag and size of the peak policy rate increase in response to an inflation innovation. Table 1 shows that the 1979.Q4–2001.Q1 calibration achieves this by setting the demand shock volatility essentially to zero, having a large volatility of supply shocks, and a somewhat smaller volatility of monetary policy shocks. The inflation expectations parameter $\zeta = 0.6$ means that the Phillips curve is strongly backward-looking for this subperiod calibration, leading to a highly persistent inflation process. While a volatile persistent component in inflation during this period is in line with a long-standing econometrics literature (Stock and Watson (2007)) and helps us match the predictability of bond excess returns, it means that there is a gap between the empirical and model impulse responses at longer horizons in the left panel of Panel D in Figure 2. We are not concerned about this discrepancy because our empirical measure of inflation combines persistent fluctuations with short-term fluctuations, which the model is not intended to capture, and because unit roots are hard to estimate and detect in finite samples.[13] Macroeconomic volatilities of annual changes in real consumption and the fed funds rate, shown in the bottom panel of Table 3, are matched closely by the model. In the model, ten-year inflation expectations are substantially less volatile than nominal ten-year Treasury yields. The model achieves this because it features endogenously time-varying risk premia in nominal Treasury bonds and because we model long-term inflation expectations as a weighted average of a slowly-moving average of past inflation and the rational forecast, with the weight on past inflation given by ζ.[14]

For the 2001.Q2–2019.Q4 subperiod, the model matches the output gap increases following inflation and interest rate surprises, though the increases in the data seem somewhat more persistent than in the model. It also matches the somewhat slower increase in the policy rate following an inflation surprise compared to the 1979.Q4–2001.Q1 subperiod. The volatilities of consumption growth, the fed funds rate, and long-term inflation expectations are also close to their empirical counterparts. As shown in the bottom panel of Table 1 the model achieves this fit for the 2001.Q2–2019.Q4 subperiod with a high volatility of demand shocks, much less volatile supply shocks, and a moderate volatility of monetary policy shocks. The monetary policy rule for this subperiod has a greater inertial parameter ($\rho = 0.8$) within the range estimated by Clarida et al. (2000), and higher output and inflation weights than the monetary policy rule in the earlier subperiod.

The model also matches the predictability of inflation forecast errors documented in the data. The last two columns in Table 2 report analogous inflation forecast error regressions in the model as in the data. In the model, we compute subjective n-quarter inflation forecasts as $\tilde{E}_t\pi_{t+n} = (1-\zeta)E_t\pi_{t+n} + \zeta\pi_{t-1-n\to t-1}$ for all n. The table shows that for the 1979.Q4–2001.Q1 calibration, the model generates predictability of inflation forecast errors from revisions in inflation forecasts, similarly to the data. While the model coefficient is even somewhat larger than in the data it is within a 95% confidence interval of the empirical estimate over the long sample 1968.Q4-2001.Q1. Intuitively, the 1979.Q4–2001.Q1 calibration features partially adaptive inflation expectations, implying that agents under-weight forward-looking

[13] Appendix Figure A1 shows the model impulse responses with $\zeta = 0$ for comparison.

[14] Our ability to match the volatility of ten-year inflation expectations does not hinge on non-rational inflation expectations. A version of the 1980s calibration with rational inflation expectations generates a very similar volatility of ten-year inflation expectations, though also less volatile nominal Treasury bond yields.

information about inflation. By contrast, the model does not generate inflation forecast error predictability for the 2001.Q2–2019.Q4 calibration, similarly to the data. This is again intuitive because the 2001.Q2–2019.Q4 calibration features $\zeta = 0$ and hence full information rational inflation expectations.

We therefore find that the model provides a good empirical fit for the main macroeconomic changes from the Volcker to the post-Volcker period. It does so through intuitive changes in parameters, indicating that demand shocks dominated in the more recent subperiod, whereas supply shocks were more important during the earlier period. The model calibration also relies on an intuitive change in the monetary policy rule, from a less inertial monetary policy rule with little weight on output gap fluctuations under Volcker, to a more gradual monetary policy rule with greater weight on output gap fluctuations more recently.

4.3 Asset Prices in the Model and in the Data

Table 3 reports key asset pricing and macroeconomic moments for both subperiod calibrations side by side with the corresponding data moments. Having already discussed the main macroeconomic moments, we now turn to the asset pricing moments shown in the top panel. The model does equally well for equity Sharpe ratios, equity volatility, and the persistence of price-dividend ratios as Campbell and Cochrane (1999) and Campbell et al. (2020), showing that adding demand shocks does not hurt the model's performance along this key dimension. Similarly to prior work, stock returns in the model are predictable from the past price-dividend ratio.[15]

The second panel reports bond moments. The 1979.Q4–2001.Q1 calibration generates a positive regression coefficient of ten-year bond excess returns with respect to the lagged slope slope of the yield curve, as in the data and as targeted in our calibration. On the other hand, the 2001.Q2–2019.Q4 calibration does not generate any such bond return predictability, which is also in line with a much weaker and statistically insignificant relationship between bond excess returns and the lagged slope of the yield curve in the 2001.Q2–2019.Q4 subperiod in the data. Figure 4 shows why we need a non-zero adaptive inflation expectations coefficient in the earlier subperiod. As we increase the inflation expectations parameter ζ, the predictability of bond excess returns increases, though only for the 1979.Q4–2001.Q1 calibration and not for the 2001.Q2–2019.Q4 calibration. In unreported results we find the model does not generate any return predictability in real bond excess returns. This is broadly in line with the empirical findings of Pflueger and Viceira (2016), who find stronger evidence

[15]While stock returns in the 1979.Q1-2001.Q1 data have a very low regression coefficient with respect to the lagged price-dividend ratio, this is partly driven by the arguably permanent shift in the level of stock prices in the mid-1990s.

for predictability in nominal than in real bond excess returns after adjusting for the time-varying liquidity differential. Figure 5 shows impulses response of the bond yield spread, decomposed into a risk-neutral (or expectations hypothesis) and a risk premium component, to each of the structural shocks in the model. Because the short-term policy rate does not contain any risk premia the risk premium component of the term spread equals the risk premium component of long-term bond yields, and hence predicts bond excess returns. The top row shows impulse responses for the 1979.Q4–2001.Q1 calibration and the bottom row shows impulse responses for the 2001.Q2–2019.Q4 calibration. The columns correspond to one-standard-deviation demand, Phillips curve, and monetary policy shocks.

The top row of Figure 5 shows that in the 1980s calibration the Phillips curve shock generates a strongly positive comovement between the yield spread and bond risk premia, showing that this shock is primarily responsible for the Campbell–Shiller bond return predictability in this subperiod calibration. Intuitively, a positive Phillips curve shock leads to a persistent increase in inflation expectations and the nominal policy rate, therefore having a relatively small effect on the risk-neutral yield spread. The risk premium therefore dominates the increases in the overall yield spread, generating a positive relationship between the yield spread and future bond excess returns. The demand shock similarly generates a positive relationship between the yield spread and bond risk premia, with no countervailing effect from the expectations hypothesis component of the yield spread. By contrast, the monetary policy shock counteracts the predictability of bond excess returns from the yield spread through its strong effect on the expectations hypothesis component.

By contrast, in the 2001.Q2–2019.Q4 calibration interest rates are less persistent and the expectations hypothesis term dominates the overall yield spread responses to all three shocks, and therefore the relationship between premia in long-term nominal Treasury bonds and the yield spread is close to zero. The model yield spread for the 2001.Q2–2019.Q4 calibration is even negatively correlated with the risk premium component, as bond risk premia are primarily driven by the more volatile demand shocks. A positive demand shock raises consumption relative to habit and makes investors less risk averse. Because nominal bonds have negative betas during this subperiod and hence have hedging value, investors' willingness to pay for this hedging value declines and the required expected excess return on Treasury bonds rises. At the same time, the yield spread falls because monetary policy raises the short-term policy rate to counteract a positive demand shock. The difference across subperiod calibrations here is reminiscent of an older literature that has documented empirically that the expectations hypothesis is a better description of the term structure of interest rates in time periods and countries where interest rates are less persistent (Mankiw et al. (1987), Hardouvelis (1994)), and Cieslak and Povala (2015)'s evidence that removing trend inflation is important for uncovering time-varying risk premia in the yield curve.

The model also captures several salient changes in ten-year Treasury bonds between the 1979.Q4–2001.Q1 subperiod and the 2001.Q2–2019.Q4 subperiod that were not targeted in the calibration. Model-implied nominal Treasury bond excess returns are extremely volatile in the 1979.Q4–2001.Q1 subperiod and much less volatile during the more recent subperiod. The slope of the yield curve is strongly positive during the 1979.Q4–2001.Q1 subperiod, and declines in the more recent subperiod, though in contrast to the data the model slope even turns negative. Further, the model-implied nominal bond beta is strongly positive in the 1979.Q4–2001.Q1 calibration and negative in the 2001.Q2–2019.Q4 calibration. Finally, the model also achieves a small but positive real bond beta during the 1979.Q4-2001.Q1 subperiod and a negative real bond beta during the more recent subperiod.[16] One slight shortcoming of the model is that in the 2001.Q2–2019.Q4 subperiod the nominal bond beta is more negative than the real one, whereas in the model both nominal and real betas are the same. We analyze in Section 5 which alternative combinations of shocks might have generated this gap between the empirical nominal and real bond betas.

5 Counterfactual Analysis and Interpreting the Post-Pandemic Regime

What drove the change from the 1980s to the 2000s and what would it take to change back to a stagflationary regime? In this section, we show how nominal and real bond betas change in the model as we vary the economy's exposure to different types of shocks, the monetary policy rule, and the rationality of inflation expectations. Throughout this counterfactual analysis, the beta of nominal bonds is of particular interest as an indicator of the risks of high inflation recessions, or stagflations.

5.1 Changing Monetary Policy, Inflation Expectations, and Shocks

Figure 6 shows the model-implied nominal and real bond betas as we change parameter groups. Panel A starts from the 1979.Q4–2001.Q1 calibration, analyzing which underlying

[16] Bond yields are almost three times as volatile as ten-year inflation expectations during the more recent subperiod calibration, thereby generating an "inflation variance ratio" of around 0.16 for the recent subperiod, in line with Duffee (2018)'s finding that habit formation models may be more able to generate volatile bond yields with less volatile inflation expectations than other leading asset pricing models. While we do not fully match the volatility of nominal bond yields in the 2000s, we do achieve a partial reconciliation of low inflation variance ratios based on partially rational inflation expectations in surveys (1979.Q4–2001.Q1 calibration) and time-varying bond risk premia (both calibrations).

macroeconomic drivers would have led to the declines in nominal and real bond betas observed in the data. The two leftmost bars in Panel A show the model nominal and real bond betas for the 1979.Q4-2001.Q2 calibration as in Table 3, and the bars to the right of the dashed horizontal line show the model-implied nominal and real bond betas as we change parameter groups to their 2001.Q2–2019.Q4 values. All other parameters are held constant at their 1979.Q4–2001.Q1 values listed in Table 1.

Most strikingly, we see that changing the shock volatilities from an economy driven by supply shocks to an economy driven by demand shocks switches both nominal and real bond betas from positive to negative, with a larger change for nominal bond betas. Moreover, only a change in the shock volatilities can generate negative nominal and real bond betas, suggesting that negative bond betas are closely linked to highly volatile demand shocks. This is intuitive, as the 1979.Q4–2001.Q1 calibration features a high volatility of supply shocks, which tend to generate high inflation and a recession, leading nominal bond prices to drop at the same time as the stock market. Setting the shock volatilities to their 2001.Q2–2019.Q4 values means that we have a high volatility of demand shocks, which generate negative real and nominal bond betas.

While the volatilities of shocks seem to matter for bond betas, other changes can also engineer a substantial decrease in the beta of nominal Treasury bonds. Increasing the monetary policy persistence parameter to its 2001.Q2–2019.Q4 value depresses nominal bond betas to nearly zero. This happens in the model because when the monetary policy rule is inertial a supply shock does not generate an immediate response of the nominal policy rate and hence only a very small output gap response. With an inertial monetary policy rule, supply shocks therefore contribute little to the covariance of nominal Treasury bond and stock returns. This can be seen from the model's 2001.Q2–2019.Q4 output gap impulse response to a Phillips curve shock in Figure 3. As in Primiceri (2006) and Bernanke et al. (1997), stagflation therefore only occurs if there is a supply shock and the Fed responds by raising interest rates. Real bond betas become positive because the real bond–stock covariance is dominated by the monetary policy shock when supply shocks have only a small effect on output and stock returns.

Conversely, Panel A of Figure 6 shows that the inflation expectations formation process and the long-term monetary policy weights on the output gap and inflation, γ^x and γ^π, matter less for bond risks. Changing the inflation expectations parameter ζ to zero so that inflation expectations are perfectly rational, as in the 2001.Q2–2019.Q4 calibration, leads to only a small decline in the model's nominal bond beta, when all other parameters are held constant at their 1979.Q4–2001.Q1 values. The intuition is that when inflation expectations are rational, a supply shock leads to a less persistent inflation response but a larger output gap response, leaving the covariance between nominal Treasury bonds and stocks roughly unchanged. Finally, changing the output gap and inflation weights in the monetary policy rule has offsetting effects, leaving nominal or real bond–stock betas roughly unchanged.

Panel B of Figure 6 illustrates our key result, namely that the counterfactuals starting from the 2001.Q2–2019.Q4 calibration are not simply the reverse of those in Panel A. In contrast to Panel A, Panel B shows that starting from the 2001.Q2–2019.Q4 calibration none of the changes to individual parameter groups has the power to flip the sign of nominal bond betas. The nominal bond–stock beta changes little if we change to a less persistent monetary policy rule, if we change the monetary policy output and inflation weights, or if we make inflation expectations adaptive. The last column in Panel B tells us that even if the shock process were to change back to the supply-shock-driven 1980s, a more gradual monetary policy could prevent nominal Treasury bonds from becoming risky. When we change the shock volatilities to the values of the 1980s calibration, nominal bond betas remain negative and decouple from real bond betas, which become positive. Real bond betas become positive because they load onto the monetary policy shock when monetary policy responds little to supply shocks, as in the 2000s calibration. While exaggerated in terms of magnitude, directionally this last counterfactual lines up well with the recent post-pandemic experience of positive real bond betas and negative nominal bond betas, as shown in Figure 1, suggesting that the post-pandemic economy likely experienced elevated supply shock volatility but that, unlike in the 1980s, the conduct of monetary policy protected nominal Treasury bonds from turning positive. Overall, these counterfactuals indicate that positive nominal bond–stock betas and stagflations are not the result of fundamental economic shocks or monetary policy in isolation, but instead require the interaction of both to create a "perfect storm".

5.2 Dissecting the Mechanism

What combination of changes would flip the nominal bond–stock beta to positive and make nominal Treasury bonds risky as in the stagflationary 1980s? This question is of relevance not only for policy makers trying to understand what drives the economy, but also for long-term investors seeking to diversify their portfolios and for the Treasury borrowing from the markets. So far, we have changed parameter groups between the values calibrated to the data for 1980s and 2000s. However, history is unlikely to repeat itself. In this Section, we therefore change parameter values one at a time and allow them to go outside their historically experienced range. Figure 7 decomposes the roles of individual shock volatilities, and Figure 8 focuses on the interaction between the volatility of supply shocks and monetary policy rule parameters, all starting from the 2001.Q2–2019.Q4 calibration.

Figure 7 varies the volatilities of individual shocks and shows the counterfactuals for nominal bond–stock betas (Panel A) and real bond–stock betas (Panel B) while holding the monetary policy rule and all other parameters constant at their 2001.Q2–2019.Q4 values. This figure shows that at the 2001.Q1–2019.Q4 monetary policy rule a decoupling of real and nominal bond-stock betas, as observed post-pandemic, indeed occurs primarily as a result of more volatile supply shocks. The middle column in Figure 7 shows that more volatile supply shocks slightly decrease nominal bond betas but leave real bond betas unchanged. The intuition goes back to the macroeconomic impulse responses in the middle column of Figure 3, where for the 2001.Q2–2019.Q4 calibration a supply shock leads to a sharp increase in inflation, a gradual increase in the nominal short-term rate, and an almost flat output gap response. Because the rise in the nominal policy rate is slow, the real rate falls initially, leading to a small increase in the output gap and then a shallow recession. Because of initially easy monetary policy, consumption rises relative to habit, making investors less risk averse and driving up stock prices just as nominal Treasury bond prices fall due to higher inflation expectations.

The other columns in Figure 7 show that an increase in the volatility of demand shocks drives down the betas of nominal and real bonds, and an increase in the volatility of monetary policy shocks drives up the betas of nominal and real bond betas, as expected. While it is somewhat hard to see in the figure, the volatility of monetary policy shocks affects the betas of real bonds more strongly, while the volatility of demand shocks affects the betas of nominal bonds more strongly. As the red dashed line shows, backward-looking inflation expectations ($\zeta = 0.9$) amplify the effect of demand shock volatility on nominal bond betas, but not on real bond betas. Intuitively, if inflation expectations are backward-looking, the same decrease in the output gap translates into a more persistent drop in inflation and this amplifies the increase in nominal bond prices.

The rightmost panel in Figure 7 shows that increasing the volatility of monetary policy shocks drives up the betas of real bonds and, to a lesser extent, the betas of nominal bonds. This is intuitive and similar to Pflueger and Rinaldi (2022), who focused on the effect of monetary policy shocks on stocks and bonds. A positive monetary policy shock leads to a decline in output and consumption through the Euler equation (14). As consumption falls toward habit, the stock market drops just as yields rise, leading bond and stock prices to fall simultaneously. The drop in the output gap leads to a slow decline in inflation through the Phillips curve (18), and so nominal bond prices fall less than real bond prices. As a result, nominal bond betas increase less strongly than real bond betas when we raise the volatility of monetary policy shocks in the model. Taken together, the discussion of Figure 7 suggests that understanding the interaction between supply shocks and the monetary policy rule is key.

Figure 8 zeroes in on this interaction, effectively asking which types of monetary policy rules would turn nominal Treasury bonds risky when there are also volatile supply shocks. This figure plots model-implied nominal bond–stock betas on the y-axis against the volatility of supply shocks on the x-axis for different monetary policy rules. The blue solid line uses the monetary policy rule from our 2001.Q2–2019.Q4 calibration. The red dashed line sets the persistence parameter to a much lower value, specifically $\rho^i = 0.5$. The yellow dotted line sets the output gap weight in the monetary policy rule to $\gamma^x = 0$. The purple line with markers sets the inflation weight in the monetary policy rule to a much higher value of $\gamma^\pi = 2$. We see that while the blue solid line is downward-sloping in the volatility of supply shocks, the three other lines are upward-sloping, indicating that several changes in the monetary policy rule can make nominal Treasury bond betas more sensitive to the volatility of supply shocks. What these three counterfactual monetary policy rules have in common is that they all imply a stronger immediate response in the nominal policy rate to supply shocks. Intuitively, if monetary policy is less inertial, less focused on output, or more focused on inflation then the policy rate rises swiftly following a positive supply shock, leading to an economic contraction and a fall in the stock market just as inflation expectations rise and nominal bond prices fall. Nominal bond prices and stocks fall simultaneously, and the nominal bond beta becomes more negative. Splitting out the effects of γ^x and γ^π shows that big changes in the inflation and output gap weights in the monetary policy rule can matter for bond risks, though the changes in γ^x and γ^π in the 1980s vs. 2000s calibrations are smaller and roughly offset each other in Figure 6. Overall, positive nominal Treasury bond betas – as observed during the stagflationary 1980s – arise in the model through the interaction of volatile supply shocks and a monetary policy rule that reacts strongly to such shocks.

6 Conclusion

This paper presents a simple model integrating a standard small-scale macroeconomic model of demand shocks, supply shocks, and monetary policy, with volatile risk premia in stocks and bonds that are linked to the business cycle. Bond and stock prices feature time-varying risk premia from consumption habits in the manner of Campbell and Cochrane (1999) and Campbell et al. (2020). Our first result is that fitting this model to macroeconomic and bond excess return predictability data separately for the 1980s and the 2000s yields an intuitive account of the changes observed in Treasury bond markets between these decades. For the 1980s, the model attributes the large and positive comovement between nominal Treasury bond returns and the stock market and the smaller but also positive comovement between real bond returns and stock returns to a dominance of supply shocks, combined with a non-inertial monetary policy rule. The intuitive model account is that during this period, a positive supply shock drives up inflation, reducing the value of nominal bonds. Monetary policy raises interest rates in response to this increase in inflation, thereby generating a recession and driving down stock prices. The declines in both bonds and stocks get amplified by risk aversion, as investors' risk aversion increases as consumption falls toward a slowly moving habit level.

For the 2000s, the model account is that volatile demand shocks, combined with a highly inertial monetary policy rule, led to negative betas for both nominal and real bonds. In our New Keynesian model with counter-cyclical risk bearing capacity, a positive demand shock drives up consumption and reduces investor risk aversion, but also drives up real and nominal interest rates, leading to declines in nominal and real bond prices. Supply shocks have little effect on the real economy because of the inertial monetary policy rule, and so nominal and real bond betas primarily reflect demand shocks.

The model also generate predictability of bond and stock excess returns, and explains the change in bond excess return predictability across the same broad time periods. We document that while bond excess return predictability from the lagged yield spread was stronger during the 1980s, it was statistically insignificant during the 2000s. The model matches these empirical findings with partially backward-looking inflation expectations during the 1980s, leading to a strongly backward-looking Phillips curve. As a result, the variation in the yield spread between long- and short-term bond yields is almost unaffected by the expectations hypothesis component, and instead dominated by time-varying risk premia, which arise endogenously in response to supply shocks. By contrast, during the 2000s supply shocks are smaller and the model inflation process is less persistent, generating a more volatile expectations hypothesis component in the yield spread and little bond return predictability, in line with the data. The model generates empirically plausible predictability in stock returns from the past price-dividend ratio and the persistence of price-dividend ratios for both subperiod calibrations.

This analysis has implications for the recent debate on whether the recent rise in inflation is likely to pre-shadow another 1980s stagflation and suggests that the nature of the monetary policy rule is crucial. During 2021 and the first half of 2022, bond betas exhibited marked differences from the 1980s, with nominal bond betas remaining low or even negative. In contrast to the 1980s, inflation-indexed or real bond–stock betas decoupled from nominal bond betas and turned positive. Our model can make sense of these movements, as it implies that in order for nominal Treasury bond betas to turn as positive as in the 1980s, and the economy to enter a similarly stagflationary regime, we would need not only volatile supply shocks but also a monetary policy rule that responds strongly to these shocks.

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Table 1: Calibration Parameters

		1979.Q4–2001.Q1	2001.Q2-2022.Q2
Consumption growth	g	1.89	
Utility curvature	γ	2	
Risk-free rate	$\bar{r}$	0.94	
Persistence surplus cons.	θ_0	0.87	
Backward-looking habit	θ_1	-0.84	
PC slope	κ	0.0062	
Consumption-output gap	ϕ	0.99	
MP inflation coefficient	γ^{π}	1.37	1.63
MP output coefficient	γ^{x}	0.40	2.00
MP persistence	ρ^{i}	0.52	0.80
Vol. demand shock	σ_x	0.02	0.60
Vol. PC shock	σ_π	0.59	0.08
Vol. MP shock	σ_i	0.50	0.29
Adaptive Inflation Expectations	ζ	0.6	0.0
Leverage parameter	δ	0.50	0.66

Consumption growth and the real risk-free rate are in annualized percent. The standard deviation σ_x is in percent, and the standard deviations σ_π and σ_i are in annualized percent. The Phillips curve slope κ and the monetary policy parameters γ^{π}, γ^{x} and ρ^{i} are in units corresponding to the output gap in percent, and inflation and interest rates in annualized percent.

Table 2: Forecast Error Regressions by Subperiod

	Data			Model	
$\tilde{E}_t\pi_{t+3} - \tilde{E}_{t-1}\pi_{t+3}$	0.926***	0.433	-0.310	1.43	-0.01
	(0.34)	(0.32)	(0.43)		
Const.	-0.114	-0.795***	-0.046		
	(0.28)	(0.20)	(0.18)		
N	126	87	71		
R-sq	0.09	0.03	0.00		
Sample	1968.Q4-2001.Q1	1979.Q4–2001.Q1	2001.Q2–2019.Q4	1979.Q4–2001.Q1	2001.Q2–2019.Q4

This table estimates Coibion and Gorodnichenko (2015) regressions of the form $\pi_{t+4} - \tilde{E}_{t+1}\pi_{t+4} = a_0 + a_1\left(\tilde{E}_{t+1}\pi_{t+4} - \tilde{E}_t\pi_{t+4}\right) + \varepsilon_{t+4}$ using quarterly GDP deflator inflation forecasts from the Survey of Professional Forecasters. Newey–West standard errors with 4 lags in parentheses. Model subjective n-quarter inflation expectations are computed assuming that inflation expectations are a weighted average of rational expectations and past average inflation $\tilde{E}_t\pi_{t+n} = \zeta\pi_{t-n-1\to t-1} + (1-\zeta)E_t\pi_{t+n}$

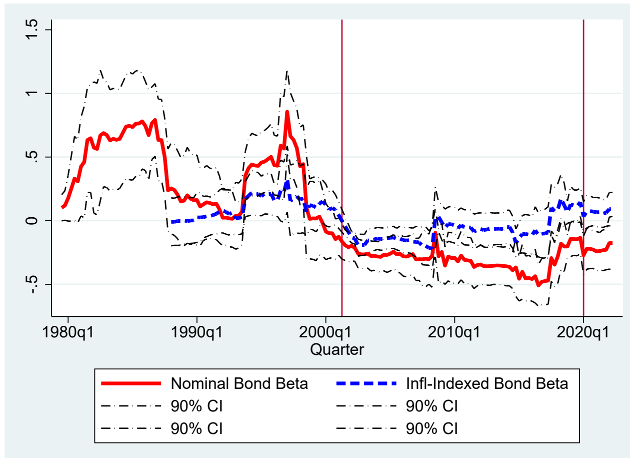
Table 3: Model and Data Moments

	1979.Q4–2001.Q1		2001.Q2–2019.Q4	
Stocks	Model	Data	Model	Data
Equity Premium	8.05	7.96	8.88	7.64
Equity Vol	16.54	16.42	18.79	16.80
Equity SR	0.49	0.48	0.47	0.45
AR(1) pd	0.96	1.00	0.93	0.84
1 YR Excess Returns on pd	-0.36	-0.01	-0.37	-0.50
1 YR Excess Returns on pd (R^2)	0.06	0.00	0.15	0.28
Bonds				
Yield Spread	2.96	1.53	-0.74	2.06
Return Vol.	17.52	14.81	2.52	9.28
Nominal bond–stock Beta	0.96	0.24	-0.11	-0.31
Real bond–stock Beta	0.04	0.08	-0.11	-0.08
1 YR Excess Return on slope	1.72	2.55	-0.20	0.86
1 YR Excess Return on slope (R^2)	0.01	0.07	0.00	0.02
Macroeconomic Volatilities				
Std. Annual Cons. Growth	0.96	1.15	1.47	1.15
Std Annual Change Fed Funds Rate	1.64	2.26	1.16	1.40
Std. Annual Change 10-Year Subj. Infl. Forecast	0.63	0.47	0.11	0.12

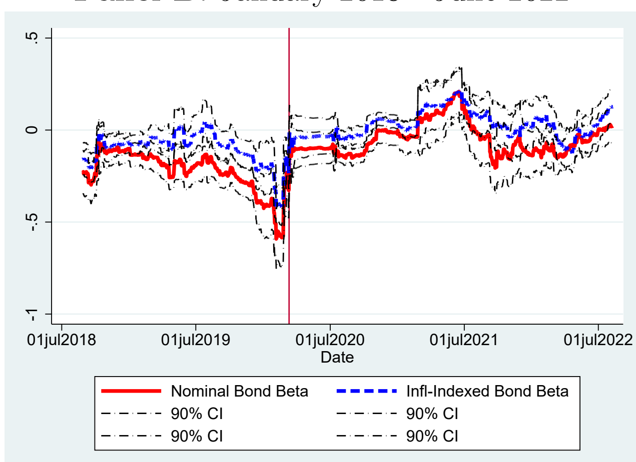
Ten-year CPI inflation expectations are from the Survey of Professional Forecasters after 1990 and from Blue Chip before that. Long-term inflation forecast available from the Philadelphia Fed research website. Model ten-year inflation expectations are computed assuming that inflation expectations are adaptive, i.e. $\tilde{E}_t \pi_{t\to t+40} = \zeta \pi_{t-41\to t-1} + (1-\zeta) E_t \pi_{t\to t+40}$, where E_t denotes rational expectations.

Figure 1: Rolling Treasury bond–stock Betas

Panel A: 1979.Q4-2022.Q2

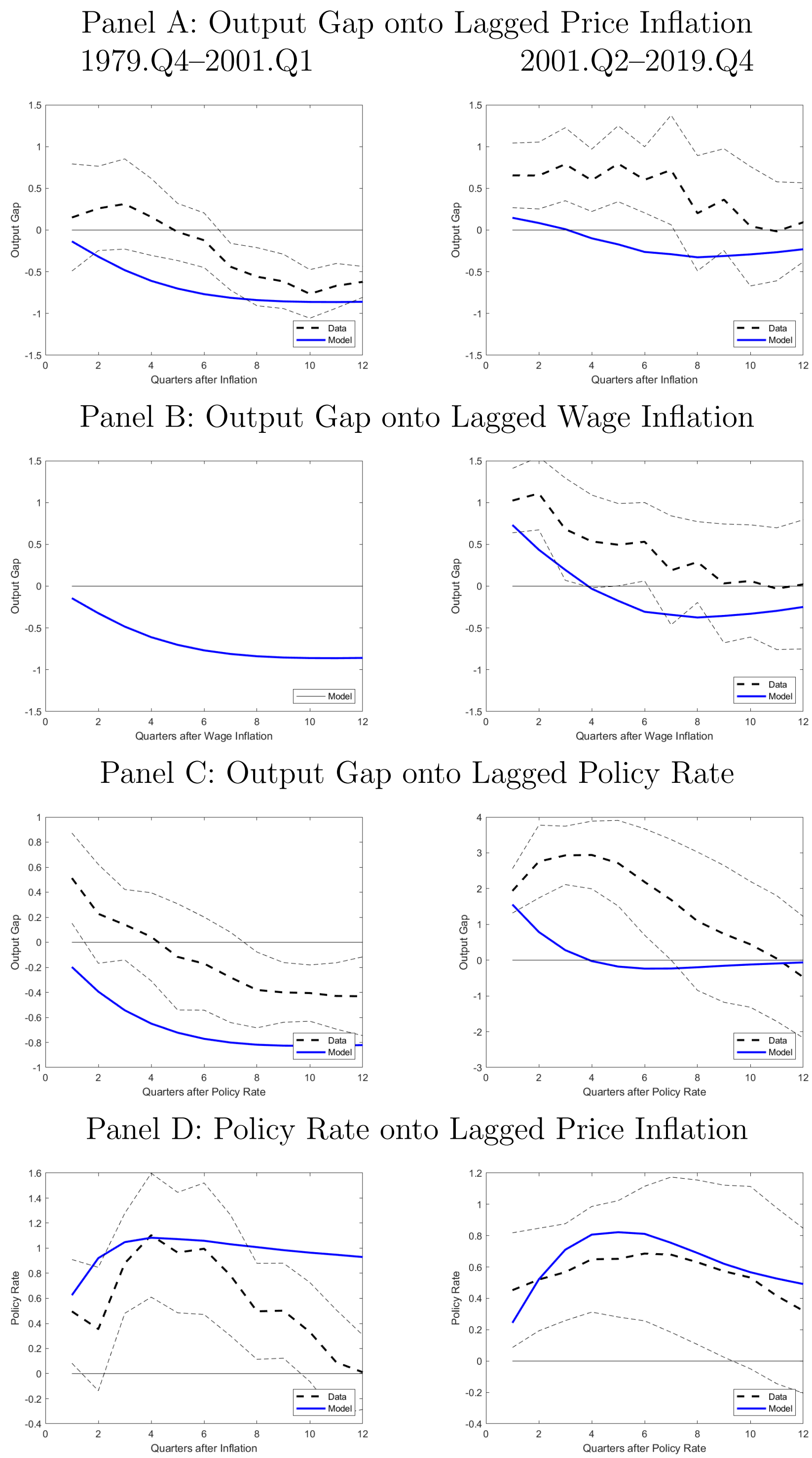


Panel B: January 2018 - June 2022



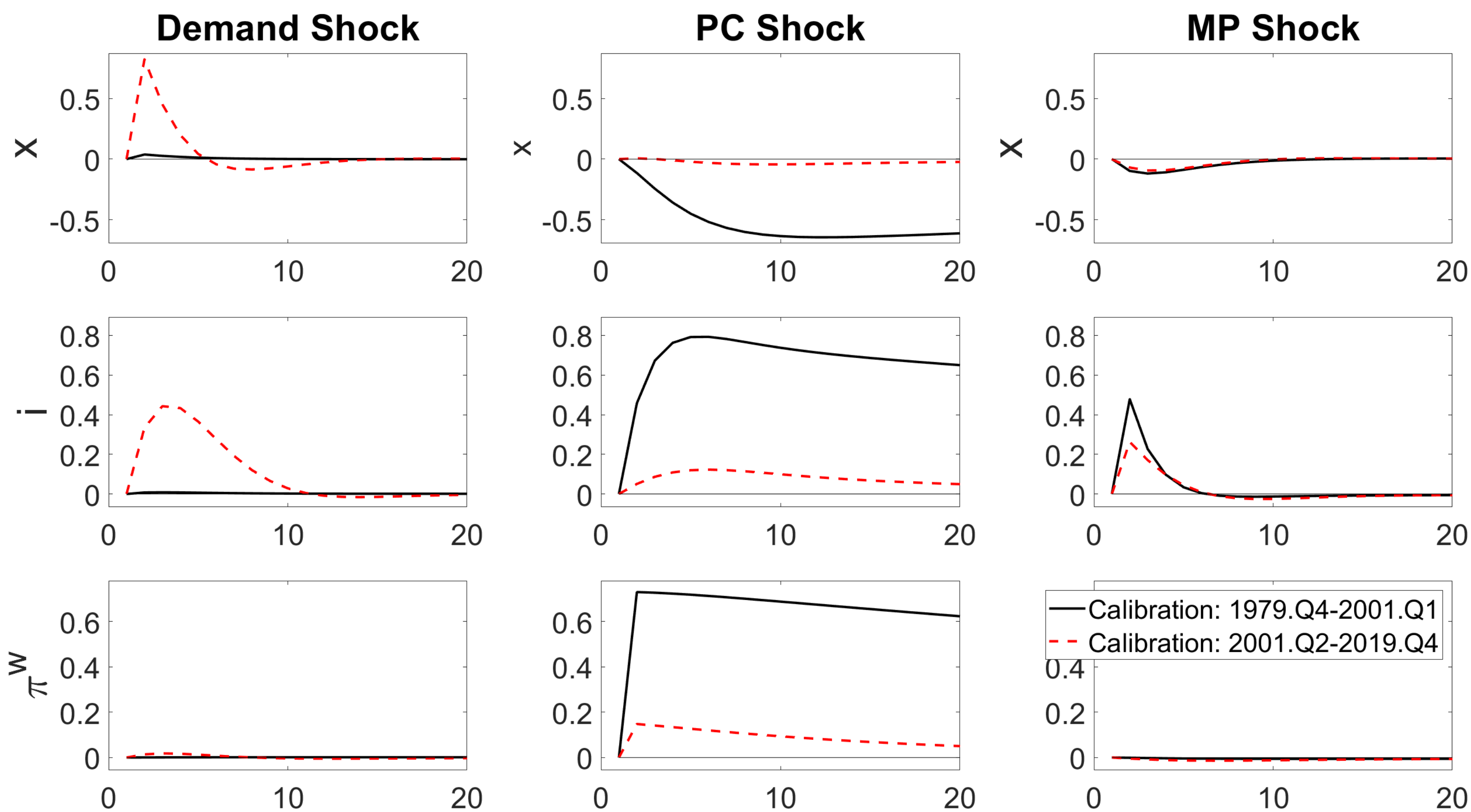
Note: Panel A shows betas from regressing quarterly ten-year Treasury bond excess returns onto quarterly US equity excess returns over five-year rolling windows for the period 1979.Q4-2022.Q2. Quarterly excess returns are in excess of three-month T-bills. Before 2001 we replace US Treasury Inflation Protected (TIPS) returns with UK ten-year linker returns. Bond excess returns are computed from changes in yields. We use zero-coupon yield curves from Gurkaynak, Sack and Wright (2006, 2008) and the Bank of England. Vertical lines indicate the start of our second sample period 2001.Q2 and the start of the pandemic 2020.Q1. Panel B shows betas from regressing daily ten-year Treasury bond log returns onto quarterly US equity log returns over 120-trading day rolling windows for the sample January 2018 through June 2022. A vertical line indicates the date when the World Health Organization declared Covid-19 a pandemic (March 11, 2020). 90% confidence intervals based on heteroskedasticiry robust standard errors are shown in dashed.

Figure 2: Empirical Output Gap, Inflation, and Policy Rate Dynamics Pre- vs. Post-2001



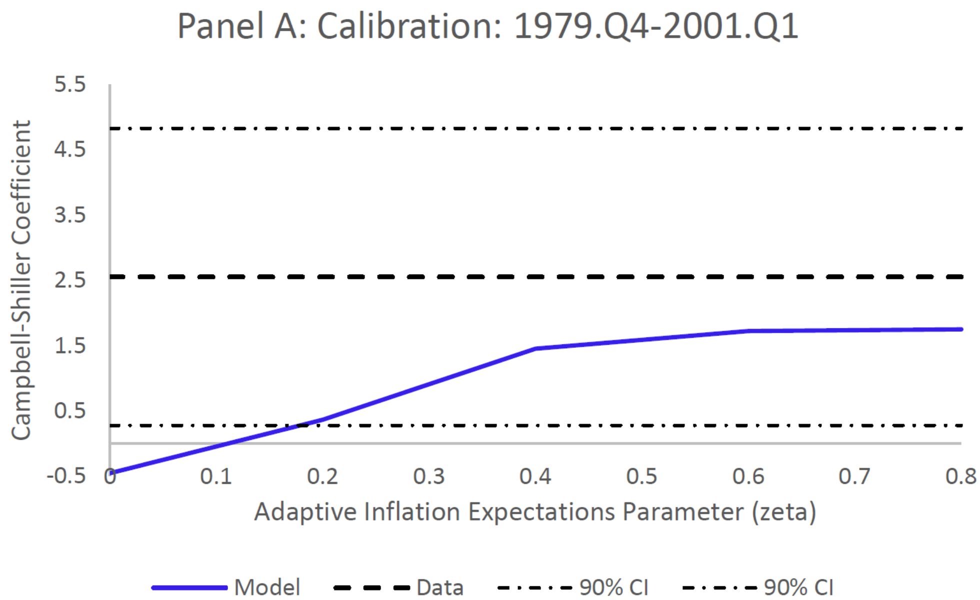
This figure shows runs quarterly regressions of the form $z_{t+h} = a_{0,h} + a_{1,h} y_t + a_{2,h} y_{t-1} + \varepsilon_{t+h}$ and plots the regression coefficient $a_{1,h}$ on the y-axis against horizon h on the x-axis in the model vs. the data. Panel A uses the output gap on the left-hand side and GDP deflator inflation on the right-hand side, i.e. $z_t = x_t$ and $y_t = \pi_t$. Panel B uses the output gap on the left-hand side and wage index inflation (ECIWAG, available starting 2000) on the right-hand side, i.e. $z_t = x_t$ and $y_t = \pi_t^w$. Panel C uses the output gap on the left-hand side and the fed funds rate on the right-hand side, i.e. $z_t = x_t$ and $y_t = i_t$. Panel D uses the fed funds rate on the left-hand side and inflation on the right-hand side, i.e. $z_t = i_t$ and $y_t = \pi_t$. Black dashed lines show the regression coefficients in the data. Thin dashed lines show 95% confidence intervals for the data coefficients based on Newey–West standard errors with h lags. Blue solid lines show the corresponding model regression coefficients averaged across 100 independent simulations of length 1000.

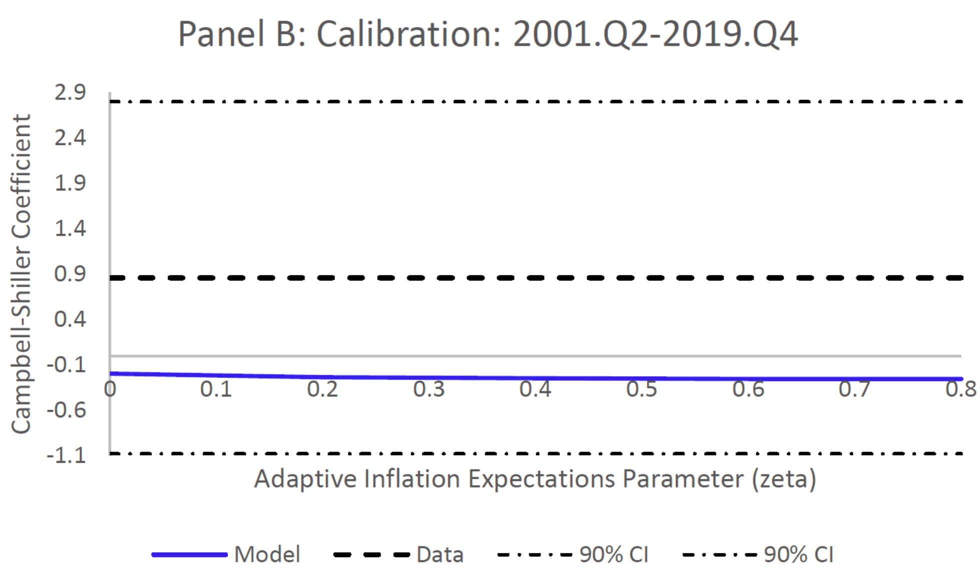
Figure 3: Model Macroeconomic Impulse Responses to Structural Shocks



This figure shows model impulse responses for the output gap (top row), nominal policy rate (middle row) and inflation (bottom row). The impulse in the left column is a one-standard-deviation demand shock, in the middle column is a one-standard-deviation Phillips curve or supply shock, and in the right column is a one-standard-deviation monetary policy shock. Impulse responses for the 1979.Q4–2001.Q1 calibration are shown in black, while the impulse responses for the 2001.Q2–2019.Q4 calibration are shown in red dashed.

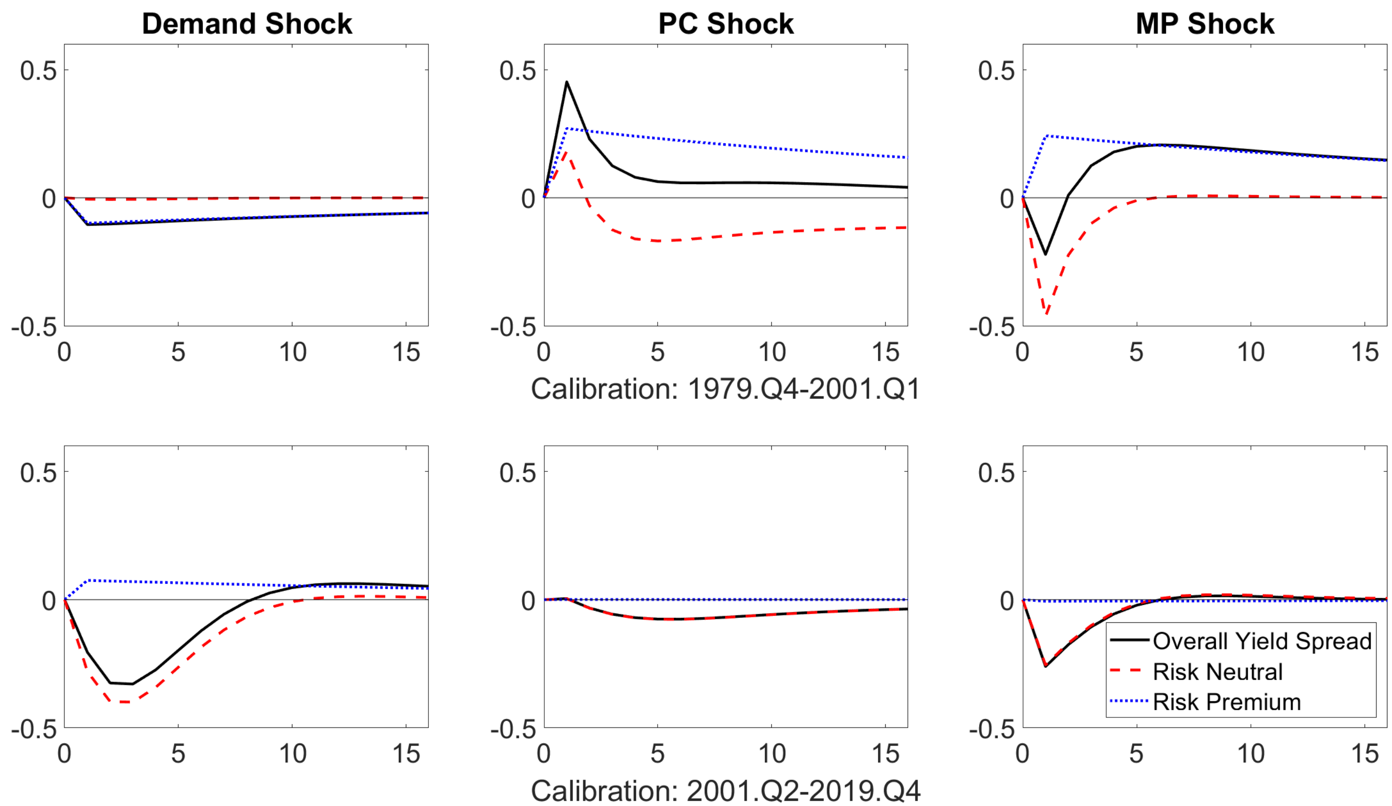
Figure 4: Campbell–Shiller Bond Return Predictability by Adaptive Inflation Expectations





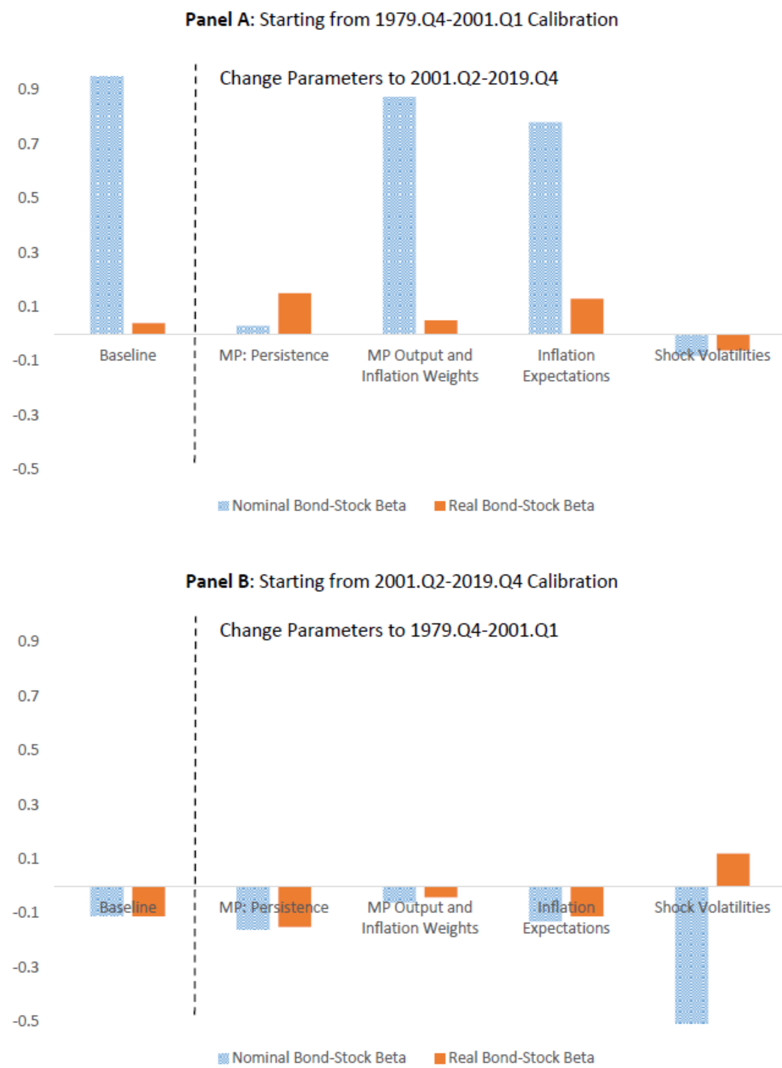
This figure shows the model Campbell–Shiller bond return predictability regression coefficient as in Table 3 against the parameter determining the adaptiveness of inflation expectations, ζ. All other parameters are held constant at their values listed in Table 1. The corresponding data moment is shown in black dashed. Data 90% confidence intervals based on Newey–West standard errors with 4 lags are shown in black dash-fot. The top panel shows data and model moments for the 1979.Q4-2001.Q calibration. The bottom panel shows model and data moments for the 2001.Q2–2019.Q4 calibration.

Figure 5: Model Bond Risk Premium Impulse Responses to Structural Shocks



This figure shows model impulse responses for the yield spread, decomposed into a risk-neutral and risk premium component. The risk neutral yield spread is computed under the expectations hypothesis. The risk premium is the difference between the overall yield spread and the risk-neutral yield spread. The top row shows impulse responses for the 1979.Q4–2001.Q1 calibration and the bottom row shows impulse responses for the 2001.Q2–2019.Q4 calibration. The impulse in the left column is a one-standard-deviation demand shock, in the middle column is a one-standard-deviation Phillips curve or supply shock, and in the right column is a one-standard-deviation monetary policy shock.

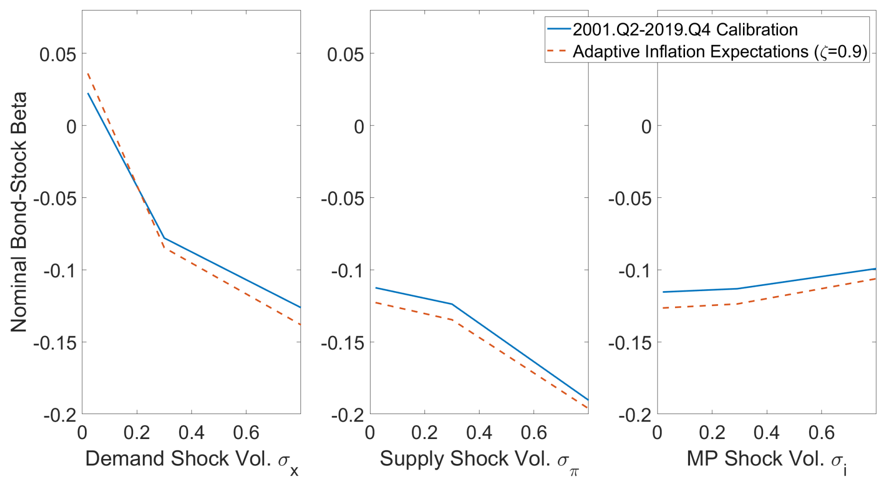
Figure 6: Counterfactuals for Nominal and Real Bond–Stock Betas



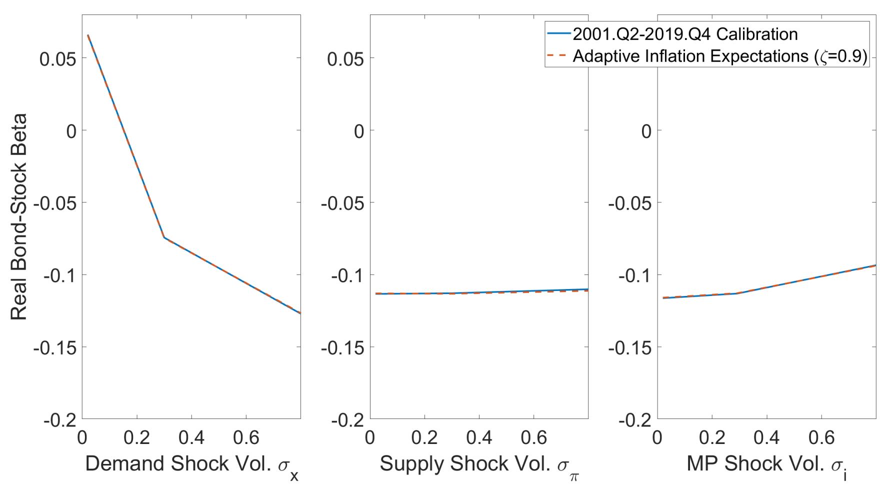
This figure shows model-implied nominal and real bond betas while changing parameter groups one-at-a-time. Panel A sets all parameter values to the 1979.Q4–2001.Q1 calibration unless stated otherwise. It then changes one at a time the following parameters to their 2001.Q2–2019.Q4 values: "MP: Persistence" (ρ^i), "MP: Output and Inflation Weights" (γ^x and γ^π), "Inflation Expectations" (ζ), and "Shock volatilities" (σ_x, σ_π, and σ_i). Panel B does the reverse exercise, holding all parameter values constant at their 2001.Q2–2019.Q4 and changing individual parameter groups to the values of the 1979.Q4–2001.Q1 calibration.

Figure 7: Varying the Volatilities of Individual Shocks

Panel A: Model Nominal Bond Beta

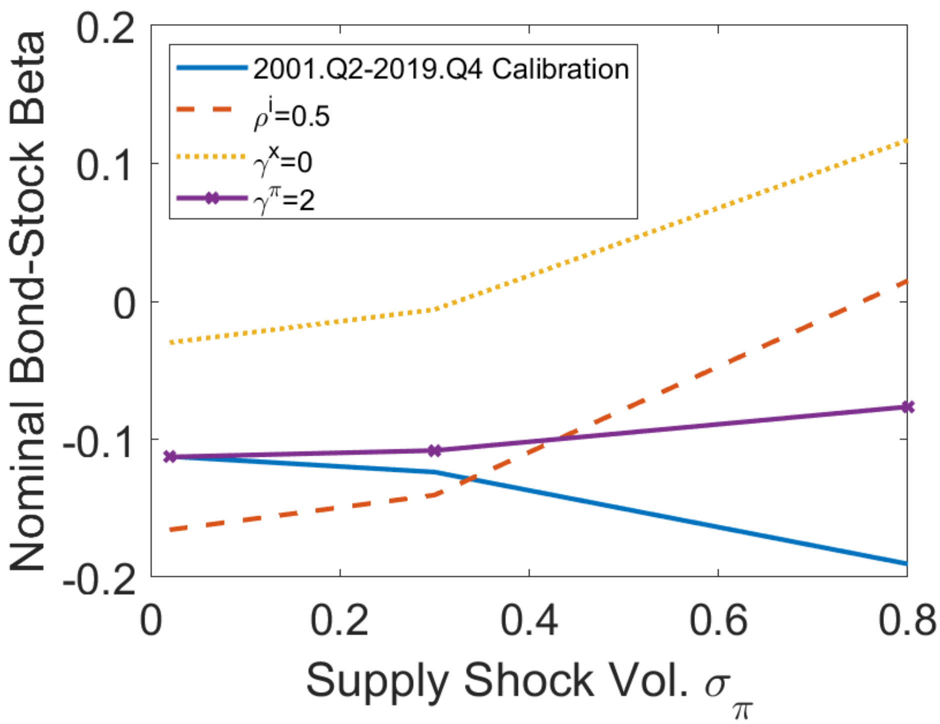


Panel B: Model Real Bond Beta



This figure shows shows model-implied ten-year nominal bond–stock betas (Panel A) and ten-year real bond–stock betas (Panel B) against the volatilities of demand shocks, supply shocks, and monetary policy shocks. The solid blue line shows comparative statics starting from the 2001.Q2–2019.Q4 calibration. The red dashed line sets the adaptive inflation expectations parameter to $\zeta = 0.9$ and the shock volatilities to the values shown on the x-axis, but all other parameter values as listed in Table 1 for the 2001.Q2–2019.Q4 calibration.

Figure 8: Interaction of Supply Shocks with the Monetary Policy Rule



This figure shows shows model-implied ten-year nominal bond–stock betas against the standard deviation of supply shocks for different monetary policy rules. Unless otherwise labeled all parameter values are set to the 2001.Q2–2019.Q4 calibration.