Adaptive Risk Preferences: Unraveling the Impact of Monetary Policy on Output

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Abstract

We introduce a novel approach for measuring time variation in habit-based preferences using corporate bond data, and employ this approach to estimate moments that describe the link between surplus consumption and output. Using a model that integrates macroeconomic dynamics with habit-based preferences, we show that our evidence on the relationship between surplus consumption and the output gap is most consistent with a model specification where a monetary policy shock of 1% reduces output by 2.2% and has a trough at 9–10 quarters. This evidence is relevant for recent studies that rely on the preference-output gap link to induce hump-shaped output responses to monetary policy shocks.

JEL Classifications: G12, G13, G22, G24

Keywords: Risk premia, default loss betas, habit formation preferences, monetary policy

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A large literature explores the impact of monetary policy on output and the contribution of monetary policy shocks to output fluctuations. Ramey (2016) reviews the leading approaches to identifying the relationship between the Fed Funds rate and output, and highlights the wide variation in the estimated responses of output to monetary policy shocks. Table 1 of her paper shows that output might drop by as much as 5% in response to a 100 basis point monetary policy shock, or as little as 0.06%. Likewise, the trough could be as short as eight months but could also be as long as two years.

These approaches often focus on modeling macroeconomic dynamics alone, with little to no emphasis on the role of time variation in risk premia. In contrast, Bauer, Bernanke, and Milstein (2023) stress that monetary policy may affect output through investors' risk preferences, such as through the risk-taking channel of Borio and Zhu (2012). Campbell, Pflueger, and Viceira (2020) introduce a novel family of consumption-based asset pricing models that link time-varying risk premia to macroeconomic dynamics through habit formation. In their model, output is assumed to affect risk preferences such that an exact macroeconomic Euler equation links real rates to the lagged, current and expected future output gap. An important benefit of this framework is that it has the potential to induce a hump shape in the impulse response function of output, and could draw out the trough by several quarters or more. Whether or not output affects risk preferences, and if it does the extent to which is affects it, is an empirical question. The challenge of previous research in addressing this question is that risk preferences are not directly observable. We overcome this challenge with a new method for measuring preferences that allows us to quantify the impact of output and lagged output on habit.

Our paper utilizes the Pflueger and Rinaldi (2022) framework, which adapts Campbell, Pflueger, and Viceira (2020) to incorporate an inertial Taylor rule and measures monetary policy shocks as deviations from the rule. Unlike Pflueger and Rinaldi (2022), however, who calibrate the model to the relationship between the Fed Funds rate and output reported by Christiano, Eichenbaum, and Evans (1999), we extract a measure of surplus consumption from the prices of corporate debt and calibrate macroeconomic dynamics to the observed relationship between surplus consumption and the output gap. Our approach yields the impulse response function of output to monetary policy shocks as a model output, rather than taking it to be a model input.

Our evidence on the relationship between surplus consumption and the output gap is most consistent with a model specification where a monetary policy shock of 100 basis points reduces output by 2.2% and has a trough at 9–10 quarters. These estimates fall within those of Christiano, Eichenbaum, and Evans (1999) who report a reduction in output by 0.7% at eight quarters and Romer and Romer (2004) who report a reduction by 4.3% at eight quarters, except for the slightly longer trough lag in our estimates.

The model matches the autocorrelation of the log surplus consumption ratio at a persistence parameter close to prior work. It produces realistic variation in consumption by reducing the standard deviation of monetary policy shocks relative to those reported by Pflueger and Rinaldi (2022). The restriction often imposed for New Keynesian models that the forward- and backward-looking terms in the Euler equation add up to one does not draw much empirical support. However, when we allow the sum of the forward- and backward-looking terms to increase slightly above one, the model provides a close approximation to the target correlation between surplus consumption and the output gap, but still slightly underestimates the correlation between surplus consumption and the twice-lagged output gap.

To extract a measure of time-varying risk premia from the prices of corporate debt, we take advantage of the fact that the cash flow of a corporate bond takes on a particularly simple form. This permits a parsimonious representation of credit spreads as a function of the default probability, the sensitivity of the default event to macroeconomic news, and the market risk premium. We estimate our measure using credit spreads for all public non-financial US firms over 1974–2021 and historical default event data dating back to 1927. Default probability estimates from Moody's Default and Recovery Database are used to create a default news index that updates in lockstep with macroeconomic news. We use the index to estimate the sensitivity of default to macroeconomic news, which we refer to as the "default loss beta," and then link it to realized default rates in a flexible manner. Our estimated default news index exhibits variation over the business cycle that is consistent with increases in the measured risk premia observed in recessions.

Our paper contributes to the literature that incorporates habit utility into a general equilibrium model of the economy, including work by Pflueger and Rinaldi (2022), Fuhrer (2000), Cochrane (2017), Campbell, Pflueger, and Viceira (2020), Smets and Wouters (2003), Smets and Wouters (2007), Swanson (2021) and Bekaert, Engstrom, and Xu (2021), and builds on the seminal work of Campbell and Cochrane (1999). Research that includes output in the habit equation (Campbell, Pflueger, and Viceira, 2020; Pflueger and Rinaldi, 2022; Pflueger, 2023) calibrates macroeconomic dynamics to one data point among a wide range of estimates on the relationship between the Fed Funds rate and output (Ramey, 2016). In contrast, we calibrate macroeconomic dynamics to the observed relationship between surplus consumption and the output gap, which allows us to quantify the response of output to monetary policy shocks in a fully integrated setting for preferences and macroeconomic fundamentals.

In addition to presenting an innovative approach to estimating the relationship between monetary policy and output, we contribute to the literature on the monetary policy transmission mechanism by estimating the relationship between monetary policy shocks and risk aversion. Previous research by Borio and Zhu (2012), Bauer, Bernanke, and Milstein (2023), Bekaert, Hoerova, and Lo Duca (2013) and Bekaert, Engstrom, and Xu (2021) suggests that time variation in risk premia is explained at least in part by changes in Federal Reserve policy. These results are consistent with studies on the stock market reaction to FOMC announcements, such as Bernanke and Kuttner (2005). Indeed, several studies find evidence that episodes of "low for long" policy lead to such a decline in risk aversion that investors reach for yield (Rajan, 2006). Dell-Ariccia, Laeven, and Marquez (2014) and Drechsler, Savov, and Schnabl (2018) model this behavior through the effects of monetary policy on bank risk-taking.

The paper proceeds as follows. Section 1 presents the model and the solution method. Section 2 describes the estimation of default loss betas. Section 3 discusses the estimation of risk premia and the how the underlying data are sourced. Section 4 computes moments that describe the comovement of risk premia and lagged output, calibrates macro dynamics to these moments, and then produces the model-implied impulse response of output to monetary policy actions. Section 5 compares our estimated impulse response of output to monetary policy actions to existing estimates, and then concludes.

1. Model

This section describes the macroeconomy, habit preferences and the stochastic discount factor (SDF). For a generic time series v_t, let $\mathbb{E}_t(v_{t+1})$ and $\sigma_{v,t}$ denote its conditional mean and standard deviation, respectively.[1] Lower-case letters indicate the log of the corresponding upper-case letters, and Δ denotes a one-period change, so that $v_t = \log(V_t)$, $\Delta v_{t+1} = v_{t+1} - v_t$, and so on. We use $\varepsilon_{v,t+1} = v_{t+1} - \mathbb{E}_t(v_{t+1}) = \Delta v_{t+1} - \mathbb{E}_t(\Delta v_{t+1})$ to denote surprise changes in v_{t+1}. Throughout, stated equations of log dynamics hold up to an additive constant. Details on the derivations are provided in Appendix A.

1A. Habit preferences

Suppose a representative agent derives utility $U_t = U(C_t)$ from real consumption C_t relative to a slowly-moving external habit level H_t, such that

$$U(C_t) \quad = \quad \frac{(C_t - H_t)^{1-\gamma} - 1}{1-\gamma}, \tag{1}$$

for some curvature parameter $\gamma > 0$. The surplus-consumption ratio, defined as $S_t = (C_t - H_t)/C_t$, measures the share of the market consumption that is available to generate utility.[2] The real SDF, denoted by M_{t+1}, has the form $M_{t+1}/M_t = U'(C_{t+1})/U'(C_t)$, up to a multiplicative constant, meaning the log SDF is given as

$$\Delta m_{t+1} \quad = \quad -\gamma \Delta \log(C_{t+1} - H_{t+1}) = -\gamma(\Delta c_{t+1} + \Delta s_{t+1}). \tag{2}$$

[1] All of our probabilistic statements are for a given probability space $(\Omega, \mathcal{F}, \mathbb{P})$ and a filtration $\{\mathcal{F}_t : t \geq 0\}$ of sub-sigma algebras of $\mathcal{F}$ satisfying the usual conditions. For details, see Protter (2005).

[2] The relative risk aversion equals $-C_t U''(C_t)/U'(C_t) = \gamma/S_t$.

Following Campbell and Cochrane (1999) and Campbell, Pflueger, and Viceira (2020), we model habits indirectly by assuming that log surplus consumption, s_t, satisfies

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

for steady-state value $\bar{s}$ of log surplus consumption, scalars θ_0, θ_1, and θ_2, and sensitivity function

$$\lambda(s_t) = \begin{cases} \frac{1}{\bar{S}}\sqrt{1-2(s_t-\bar{s})}-1, & s_t \leq s_{max} \\ 0, & s_t > s_{max}, \end{cases} \tag{4}$$

where σ_c is the conditional standard deviation of surprise consumption growth $\varepsilon_{c,t+1}$, $\bar{S} = \sqrt{\gamma/(1-\theta_0)}\sigma_c$, and $s_{max} = \bar{s} + \frac{1}{2}(1-\bar{S}^2)$. The consumption surprise $\varepsilon_{c,t+1}$ is an equilibrium object depending on fundamental shocks. We will show that in our solution, it is conditionally normally distributed and homoskedastic.

Relative to Campbell and Cochrane (1999), Campbell, Pflueger, and Viceira (2020) introduce the terms $\theta_1 x_t + \theta_2 x_{t-1}$, where x_t (relative to a steady state) equals stochastically detrended log real consumption,

$$x_t = c_t - (1-\phi)\sum_{j=0}^{\infty}\phi^j c_{t-1-j}, \tag{5}$$

where ϕ is a smoothing parameter. Pflueger and Rinaldi (2022) emphasize that a non-zero value for θ_1 is necessary to generate a hump-shaped output response to a monetary shock and estimate its value by calibrating the model such that it generates the hump. In contrast, we estimate θ_1 from the moments of our risk aversion measure and use it to examine the shape of the output response. Pflueger and Rinaldi (2022) present microfoundations under which x_t also equals the log output gap, that is, the difference between between log output and log potential output under flexible prices. Equation (5) implies

$$\mathbb{E}_t(\Delta c_{t+1}) \quad = \quad \mathbb{E}_t(x_{t+1}) - \phi x_t. \tag{6}$$

1B. Euler equation

The real risk-free rate r_t satisfies the asset pricing first-order condition

$$1 \quad = \quad \mathbb{E}_t\left(\frac{M_{t+1}}{M_t}\exp(r_t)\right) = \mathbb{E}_t\left(\exp(\Delta m_{t+1} + r_t)\right), \tag{7}$$

which implies the Euler equation for real risk-free rates:

$$r_t \quad = \quad -\log\left(\mathbb{E}_t(\exp(\Delta m_{t+1}))\right). \tag{8}$$

Substituting (2), (3) and (4) into (8), and simplifying, gives

$$r_t \quad = \quad \gamma\,\mathbb{E}_t(\Delta c_{t+1}) + \gamma\theta_1 x_t + \gamma\theta_2 x_{t-1}. \tag{9}$$

Plugging (6) into (9), and rearranging terms, yields

$$x_t \quad = \quad f_x\,\mathbb{E}_t(x_{t+1}) + \rho_x x_{t-1} - \psi r_t, \tag{10}$$

where $\psi = \frac{1}{\gamma(\phi-\theta_1)}$, $f_x = \gamma\psi$ and $\rho_x = \theta_2\gamma\psi$. A given sum of the forward- and backward-looking terms in (10), denoted by $\alpha = f_x + \rho_x$, implies the relationship

$$\theta_2 \quad = \quad \alpha(\phi - \theta_1) - 1. \tag{11}$$

Some New Keynesian models assume that the forward- and backward-looking terms add up to one ($\alpha = 1$).[3] This restriction is also imposed by Pflueger and Rinaldi (2022). In contrast, the

[3] See, for example, Dennis (2009).

macro dynamics in Campbell, Pflueger, and Viceira (2020) are consistent with $\alpha = 1.04$. Because we estimate θ_1 and θ_2 to match the moments of the risk aversion measure, we do not impose any restriction on α. Nonetheless, our estimates show that it is fairly close to one.

1C. Phillips curve

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

$$\pi_t = f_\pi \mathbb{E}_t(\pi_{t+1}) + \rho_\pi \pi_{t-1} + \kappa x_t, \tag{12}$$

for constants f_π, ρ_π and κ. Following the arguments in the appendix to Pflueger and Rinaldi (2022), Equation (12) can be derived from microfoundations, where κ is a price-flexibility parameter and the aggregate resource constraint implies that output equals consumption. The restriction common for New Keynesian models that the forward- and backward-looking terms add up to one applies: $f_\pi + \rho_\pi = 1$.

1D. Monetary policy rule

Let i_t denote the nominal risk-free rate between t and $t+1$, and let $i_t^* = \psi_\pi \pi_t + \psi_x x_t$ denote the nominal policy rate. Monetary policy is described by the rule

$$i_t = \rho_i i_{t-1} + (1-\rho_i) i_t^* + v_t, \tag{13}$$

for some inertia parameter $\rho_i \in (0,1)$.

To make the dynamics of inflation and interest rates tractable, we approximate the log one-period nominal interest rate as the log real rate plus expected log inflation:

$$r_t = i_t - \mathbb{E}_t(\pi_{t+1}). \tag{14}$$

1E. Equilibrium solutions

The macroeconomic state vector is given as $Z_t = [x_t, \pi_t, i_t]'$. Its elements are normalized to have zero averages. The fundamental shock is ε_t. We are interested in a equilibrium solution of the form

$$Z_t = BZ_{t-1} + \Sigma \nu_t, \tag{15}$$

where B and Σ are $[3 \times 3]$ and $[3 \times 1]$ matrices, respectively. There may exist alternative equilibrium dynamics for Z_t, with additional lags or sunspot shocks, but characterization of these additional equilibria is beyond the scope of this paper. We follow the procedure in Pflueger and Rinaldi (2022) to choose among equilibria of the form (15). Specifically, we narrow the set of equilibria by requiring that all eigenvalues of B must be less than one in absolute value. In our applications, there exist exactly three generalized eigenvalues with absolute value less than one, and we pick the non-explosive solution corresponding to these three eigenvalues.

1F. Asset prices and risk premia

In frictionless markets, the real market value at time t of a claim to a real cash-flow process Y_t is

$$V_{Y,t} = \sum_{j=1}^{\infty} \mathbb{E}_t(\exp(\sum_{s=1}^{j} m_{t+s})\, Y_{t+j}). \tag{16}$$

It can be expressed as

$$V_{Y,t} = \mathbb{E}_t(\exp(m_{t+1}))\, \mathbb{E}_t(Y_{t+1} + V_{Y,t+1})\, (1 - \text{prem}_{Y+V_Y,t}), \tag{17}$$

where $\mathbb{E}_t(\exp(m_{t+1}))\, \mathbb{E}_t(Y_{t+1} + V_{Y,t+1})$ is the value of Y that would apply if consumers were risk neutral, and $\text{prem}_{Y+V_Y,t}$ denotes the one-period risk premium on the claim to Y.[4] In Appendix A,

[4] Note that $\text{prem}_{Y+V_Y,t} = 1 - R_{f,t}/\mathbb{E}_t(R_{Y,t+1})$, where $R_{Y,t+1} = (Y_{t+1} + V_{Y,t+1})/V_{Y,t}$ is the one-period gross return on Y, and $R_{f,t}$ is the one-period gross return on the risk-free asset. As long as the expected excess return on Y is near zero, the approximate relationship $\text{prem}_{Y+V_Y,t} = \log(\mathbb{E}_t(R_{Y,t+1})) - r_{f,t}$ holds.

we derive the approximate relationship

$$\text{prem}_{Y+V_Y,t} \quad = \quad \beta_{Y,t}\, \text{prem}_t, \tag{18}$$

where

$$\beta_{Y,t} \quad = \quad \frac{\text{Cov}_t\left(\varepsilon_{c,t+1}, \frac{Y_{t+1}+V_{Y,t+1}}{\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})}\right)}{\sigma_c^2} \tag{19}$$

is the claim's consumption news beta, and

$$\text{prem}_t \quad = \quad \gamma(1+\lambda(s_t))\sigma_c^2 \tag{20}$$

is the risk premium for the one-period consumption claim or, more generally, the risk premium on a one-period beta-one claim.

Substituting (4) into (20) gives the approximate relationship

$$\log(\text{prem}_t) \quad = \quad -s_t, \tag{21}$$

which holds when s_t is close to its steady state $\bar{s}$, and up to a constant. In the remainder of this section and the next, we describe how we extract $\log(\text{prem}_\text{t})$, and thus, s_t, from corporate bond data. With this in hand, we are able to estimate parameters in the surplus consumption equation (3), and ultimately to identify the relationship between interest rates and output.

1G. Corporate bonds

While the pricing concept (16)–(20) applies to all assets, it is particularly insightful when applied to corporate debt where the cash-flow process Y takes on a simple form. Consider a firm i that is solvent at time t and which owes one dollar of principal on a zero-coupon bond with a maturity date of $t+1$. If it defaults, investors experience a loss of $L_{i,t+1}$, which denotes the fractional loss of a dollar owed in time-$(t+1)$ dollars. If the firm survives, $L_{i,t+1}=0$. The real market value of the bond is

$$B_{it} \quad = \quad \mathbb{E}_t(\exp(m_{t+1}))(1-\text{cs}_{it}), \tag{22}$$

where cs_{it} denotes the one-period credit spread that is given as

$$\text{cs}_{it} \quad = \quad \mathbb{E}_t(L_{i,t+1})+\mathbb{E}_t(1-L_{i,t+1})\,\text{prem}_{1-L,it}. \tag{23}$$

The credit spread in excess of expected losses is measured by $\text{cs}_{it}-\mathbb{E}_t(L_{i,t+1})$. We distinguish between observed credit spreads, denoted by $\widehat{\text{cs}}_{it}$, and the model-based spreads cs_{it} in (23), to allow for observed excess spreads $\widehat{\text{cs}}_{it}-\mathbb{E}_t(L_{i,t+1})$ to include a proportional illiquidity mark-up $\exp(\ell_{it})$, so that

$$\widehat{\text{cs}}_{it}-\mathbb{E}_t(L_{i,t+1}) \quad = \quad \mathbb{E}_t(1-L_{i,t+1})\,\text{prem}_{1-L,it}\,\exp(\ell_{it}). \tag{24}$$

When there are no illiquidity effects ($\ell_{it}=0$), bonds trade at efficient market levels ($\text{cs}_{it}=\widehat{\text{cs}}_{it}$). However, when there are carrying costs for holding default insurance ($\ell_{it}>0$), defaultable bonds trade at below-efficient market levels ($\text{cs}_{it}>\widehat{\text{cs}}_{it}$).

Equation (24) gives observed excess spreads, per unit of expected losses, as

$$\frac{\widehat{\text{cs}}_{it}-\mathbb{E}_t(L_{i,t+1})}{\mathbb{E}_t(L_{i,t+1})} \quad = \quad -\beta_{L,it}\,\text{prem}_t\,\exp(\ell_{it}), \tag{25}$$

where $\beta_{L,it}=-(\mathbb{E}_t(1-L_{i,t+1})/\,\mathbb{E}_t(L_{i,t+1}))\beta_{1-L,it}$ is the consumption news beta for the default loss claim, or "default loss beta" for short. A negative $\beta_{L,it}$ reflects the common notion that default insurance is more likely to pay in "bad" economic states than in "good" states.

2. Default Loss Betas

Our ultimate goal is to identify prem_t in Equation (25), up to a multiplicative constant. This requires estimates of default loss betas,

$$\beta_{L,it} = \frac{1}{\sigma_c^2}\text{Cov}_t\left(\varepsilon_{c,t+1}, \frac{L_{i,t+1}}{\mathbb{E}_t(L_{i,t+1})}\right). \tag{26}$$

Due to the infrequency of default events, especially for good and medium credit quality firms, estimating $\beta_{L,it}$ for individual firms is unlikely to yield robust results. We therefore assume that the default loss beta of an individual firm is described well by the average beta of a group of similar firms. Specifically, we use $j_{\cdot t}$ to index a time-t partition of firms into J non-overlapping cohorts, and j_{it} to denote the cohort that firm i belongs to at time t. We take $L_{j,t+1}$ to be the realized average fractional loss of bond notional in time-$t+1$ dollars among firms that belong to cohort j at t. Consistent with (19), we set $\beta_{L,it} = \beta_{L,j_{it}t}$ where

$$\mathbb{E}_t\left(\frac{L_{j,t+1}}{\mathbb{E}_t(L_{j,t+1})} - 1 \middle| \varepsilon_{c,t+1}\right) = \beta_{L,j_{it}t}\varepsilon_{c,t+1}. \tag{27}$$

To estimate β we require a measure of shocks that are related to default risk. Hilscher and Wilson (2017) show that credit ratings are strongly related to systematic risk. Thus, we build an index that represents variation in systematic default risk using credit ratings. In particular, for each rating category (i.e., for each cohort j_t), we calculate the unexpected default rate and build a default news index as the weighted average of these cohort-specific shocks.

Define $\zeta_{j,t+1}$ as the realized average rate of default by time $t+1$ among firms that belong to rating cohort j at t, and $P_{jt} = \mathbb{E}_t(\zeta_{j,t+1})$ as the associated expected cohort-wide default rate. Importantly, in estimating cohort-level default rates we link default rates to market conditions, meaning our default predictions update through the business cycle. For a constant expected recovery of notional in the event of default or, more generally, as long as expected recovery rates are independent of realized default rates, $L_{j,t+1}/\mathbb{E}_t(L_{j,t+1}) = \zeta_{j,t+1}/P_{j,t}$ holds and (27) links unexpected defaults to consumption news via

$$\mathbb{E}_t \left(\frac{\zeta_{j,t+1}}{P_{jt}} - 1 \middle| \varepsilon_{c,t+1} \right) = \beta_{L,jt} \varepsilon_{c,t+1}. \tag{28}$$

Across cohorts, we observe countercyclical increases in unexpected defaults, indicating that default news for a cohort reflects systematic risk that can be captured by a single index. Thus, we assume there exists a weighted average of cohort-specific default shocks that covaries with default risk in the economy:

$$z_{t+1} = \sum_{j=1}^{J} \omega_j \left(\zeta_{j,t+1} - P_{jt} \right), \tag{29}$$

Therefore, this default news index also varies with consumption news. That is, for some positive scalar b,

$$\mathbb{E}_t \left(z_{t+1} \middle| \varepsilon_{c,t+1} \right) = -b \varepsilon_{c,t+1}. \tag{30}$$

Assuming that all of the systematic default risk of a cohort is a function of the default news index, we can use the loadings on the index, K_{jt}, to calculate $\beta_{L,jt}$. Specifically, we assume

$$\mathbb{E}_t \left(\zeta_{j,t+1} - P_{jt} \middle| \varepsilon_{c,t+1}, z_{t+1} \right) = K_{jt} \, z_{t+1}, \tag{31}$$

This allows us to compute β as:

$$\beta_{L,jt} = -b \frac{K_{jt}}{P_{jt}}. \tag{32}$$

The vector of primitive model parameters is

$$(\kappa, \rho, \{\omega_j\}, \{K_j\}). \tag{33}$$

2A. Default news

We now describe the process for measuring cohort-specific default news $\zeta_{j,t+1} - P_{jt}$ in (30), which relies on realized default data reported in Moody's Default and Recovery Rate Database. We express $\zeta_{j,t+1}$ and P_{jt} in annualized form and, for robustness purposes, measure them using their annualized five-year counterparts. To do so, first, we filter the entire Moody's database for US non-financial corporates. For each letter[5] rating and beginning of month, we compute the realized cumulative default rate over the next five years, as shown in Figure 1.

To predict defaults, we assume that the default rate can be described as a function of the past year's stock returns. We obtain the value of the S&P 500 index from CRSP and calculate the trailing one-year return for each month t. We merge the stock return data with the Moody's default rate data for a panel data set that covers January 31, 1927 onwards.

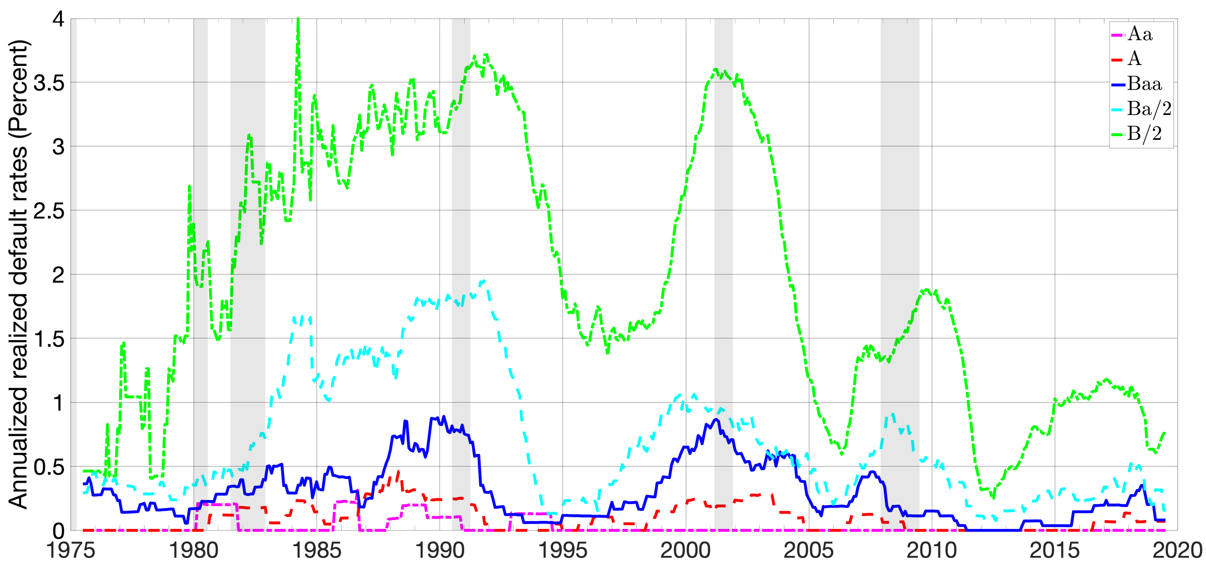

Figure 1: Realized default rates

The figure shows the monthly times series of annualized five-year realized default rate by letter rating cohort. The underlying data are sourced from the Moody's Default and Recovery Rate Database, filtered for US non-financial corporates. For the high-yield cohorts, the displayed realized default rates are scaled by a factor of one-half. The sample dates t run from January 1, 1973 to January 1, 2017, and the associated default rates are shown in the figure as of time $t+2.5$. The shaded areas indicate NBER recessions.

Next, for each month from January 1973 onwards, we estimate a beta regression model of past five-year default rates on stock index returns. These regressions are estimated using all available

[5] Alphanumeric ratings that refine major rating categories were introduced in 1983. So, for consistency over time, we group firms by letter rating categories instead of alphanumeric rating categories.

data as of the beginning of the month. Thus, for January 1, 1973, the default data for the regression starts on January 31, 1927 and ends on December 31, 1967, whereas for February 1, 1973, the data also start from January 31, 1927 but end on the last day of January 1968, and so on. Each end-of-month t (or, equivalently, beginning-of-month $t+1$), we use the estimated beta regression and the S&P500 return observed at end-of-month t to compute P^5_{jt} as the predicted five-year cumulative default rate for cohort j. Annualized five-year rates are given as $P^{5a}_{jt} = 1-(1-P^5_{jt})^{1/5}$.

Figure 2 shows the monthly time series of estimated P^{5a}_{jt} by letter rating j. For investment-grade categories, we observe a slightly decreasing trend in cohort-level probabilities over time. For high-yield cohorts, estimates trend higher, especially from the early 1990s to the GFC for the lowest rating category.

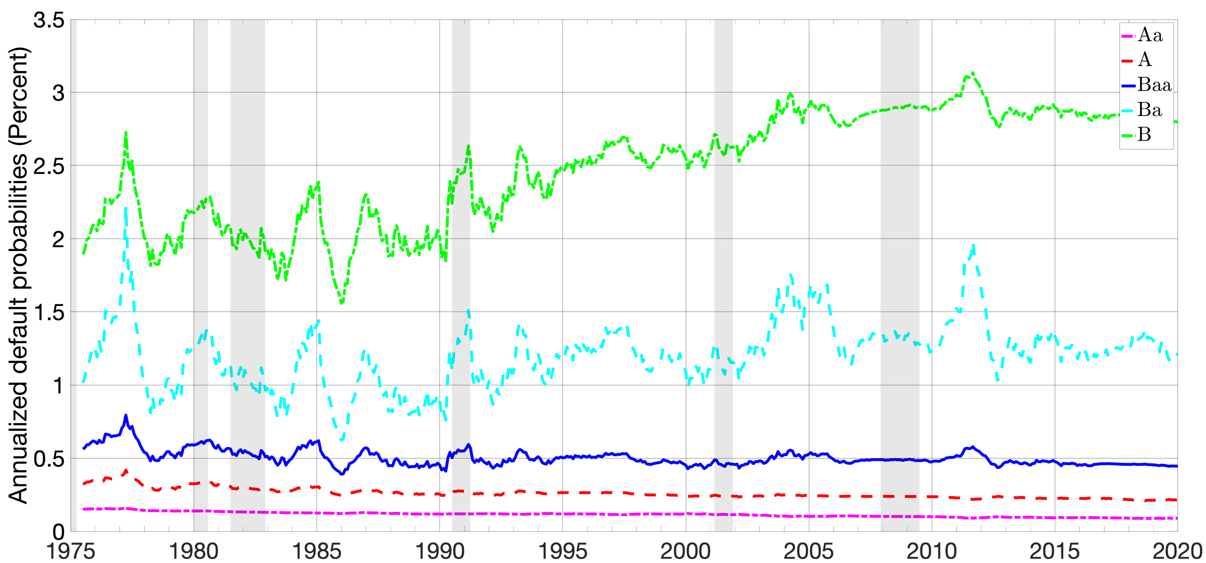

Figure 2: Probabilities of default

The figure shows the monthly times series of annualized five-year default probabilities P^{5a}_{jt} by letter rating cohort j. The underlying data are sourced from the Moody's Default and Recovery Rate Database and CRSP. The sample dates t run from January 1, 1973 to January 1, 2017, and the associated default probabilities are shown in the figure as of time $t+2.5$. The shaded areas indicate NBER recessions.

2B. Calibration

Using the predicted and actual default rates ($\zeta_{j,t+1}$ and P_{jt}), Figure 3 shows the cohort-specific default news, $\zeta_{j,t+1} - P_{jt}$. The graph shows considerable common cyclicality in default news across cohorts.

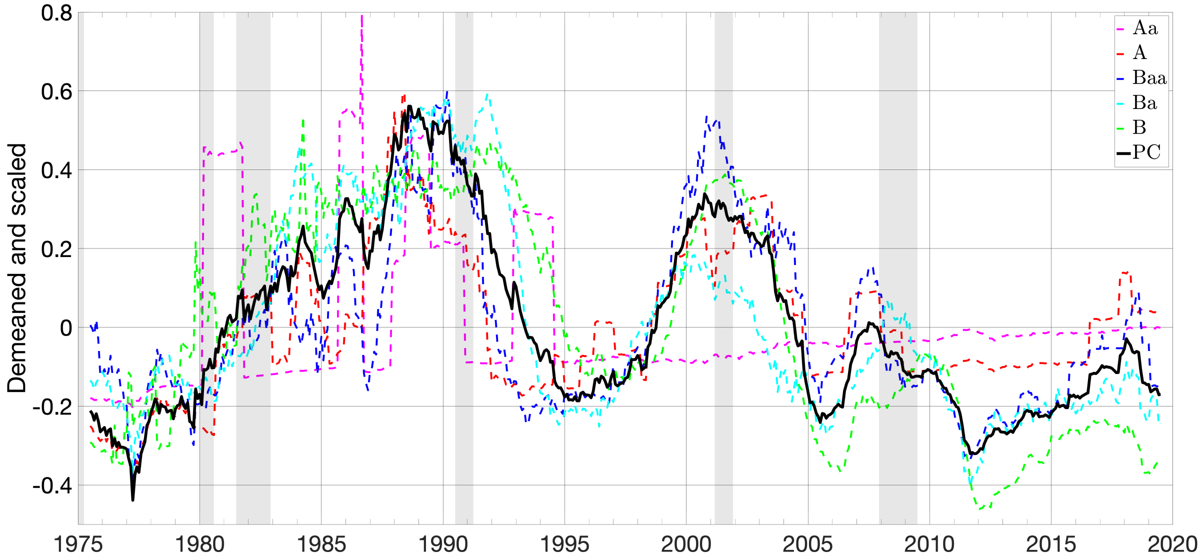

Figure 3: Default news

The figure shows the monthly time series of default news, $\zeta_{j,t+1} - P_{jt}$, for Moody's letter rating cohorts. Annualized realized default rates $\zeta_{j,t+1}$ are proxied as annualized five-year average default rates starting with month-end t, and annualized default probabilities P_{jt} are proxied by annualized five-year average default rates. The sample dates t run from January 1, 1973 to January 1, 2017, and the associated default news $\zeta_{j,t+1} - P_{jt}$ are shown in the figure as of time $t+2.5$. The first principal component (PC) is shown in black. All time series are demeaned and scaled by their max-min range. The shaded areas indicate NBER recessions.

The default news index, introduced in Equation (29), is constructed as a weighted average of cohort-specific default news. Using T to denote the length of our sample period, the non-negative weights ω_{jt} are subject to the constraint $\sum_{j,t} \omega_{jt}/T = 1$. This "adding-up constraint" is less strict than requiring $\sum_{j,t} \omega_{jt} = 1$ to hold for all t. This is to allow for the possibility that a default news index that satisfies (30) may exhibit greater time variation than, for example, the first principal component of cohort-specific default news.[6]

As can be seen from Figure 3 default news tends to vary more for riskier firms. We therefore consider the specification

$$\omega_{jt} = \omega_j P_{jt}^{\rho} \qquad \text{and} \qquad K_{jt} = \frac{K_j P_{jt}^{\kappa}}{\sum_{j=1}^{J} \omega_j K_j P_{jt}^{\kappa+\rho}}, \tag{34}$$

for scalars κ and ρ, and cohort fixed effects ω_j and K_j.

[6] Principal components of cohort-specific default news are given as weighted averages across cohorts j of $\zeta_{j,t+1} - P_{j,t}$, with weights that are time invariant. While (29) nests the case where z_t is a principal component, it is more general in that it also allows for time variation in cohort weights.

We estimate $(\kappa, \rho, \{\omega_j\}, \{K_j\})$ from non-linear regressions, as follows. We set the weights ω_j used to construct the default news index in (29) to ω_{IG} if j is an investment-grade category and to ω_{HY} if j is a high-yield category. For fixed values of κ, ρ and ω_{IG}, we solve for ω_{HY} using the definition of $\omega_{j,t}$ in (34) and the constraint $\sum_{j,t} \omega_{jt}/T = 1$.

Given κ, ρ and the set of ω_j's for all cohorts j, labeled $\{\omega_j\}$, the unknown coefficients K_{jt} in (32) are given as functions of $\{K_j\}$ (as per (34)). Jointly for all cohorts j, we search for the set of values K_j that minimizes the sum of squared errors in (31). This involves an iterative search that starts with an initial choice $\{K_j^{(0)}\}$. Without loss of generality, we choose $\{K_j^{(0)}\}$ such that $\sum_{j=1}^J K_j^{(0)} = 1$. Given $\{K_j^{(n)}\}$ in iteration n, for each cohort j we find the value $K_j^{(n+1)}$ so that $\sum_t e_{j,t+1}^2$ is minimized, where

$$e_{j,t+1} \quad = \quad (\zeta_{j,t+1} - P_{jt}) - K_j^{(n+1)} \left[\frac{P_{jt}^{\kappa}}{\sum_{j=1}^J \omega_j K_j^{(n)} P_{jt}^{\kappa+\rho}} z_{t+1} \right]. \tag{35}$$

We stop the iterations once $\{K_j^{(n+1)}\}$ remains (nearly) unchanged from $\{K_j^{(n)}\}$.

Next, we iterate over different choices for κ, ρ and ω_{IG} to find the closest cross-cohort fit in (31). In our calibrations, we assess the cross-cohort closeness of fit by the average scaled root mean squared error:

$$\frac{1}{J} \sum_{j=1}^{J} \frac{\sqrt{\sum_t e_{j,t+1}^2}}{\sqrt{\sum_t (\zeta_{j,t+1} - P_{jt})^2}}. \tag{36}$$

In (36), we scale cohort-specific sums of squared errors by the corresponding sum of squared default news. This is done to control for cross-cohort heterogeneity in the level of uncertainty associated with default predictions.

The estimates of $(\kappa, \rho, \{\omega_j\}, \{K_j\})$ are shown in Table 1. Panel A reports the parameters related to the default news index, and Panel B shows the parameters used to construct default betas in (32). The table shows that the loadings on the default news index are larger for lower-credit-quality cohorts. Given our assumptions and the positive value of κ in the table, this implies that

Table 1: Default loss beta calibration results

Index parameters				Default loss beta parameters					
κ	ρ	ω_{IG}	ω_{HY}	K_{Aa}	K_A	K_{Baa}	K_{Ba}	K_B	sRMSE
0.359	-0.216	0.091	0.021	0.017	0.045	0.088	0.331	0.519	0.581

The table reports the fitted model parameters in (33). The calibration results are obtained by minimizing the average scaled root mean squared error (sRMSE) in (36).

default loss betas $\beta_{L,jt}$ in (32) are more negative for riskier firms.

The default news index z_{t+1} constructed from the parameters in Panel A of Table 1 is shown in Figure 4. The figure shows the default news index in black for each month from 1975 to 2017, as well as the first principal component of unexpected defaults across rating cohorts. The graph shows considerable cyclicality in the index, supporting our view that it represents the systematic component of cohort-level default risk. The default news index and the principal component track each other closely, meaning there is limited temporal variation in cohort weights.

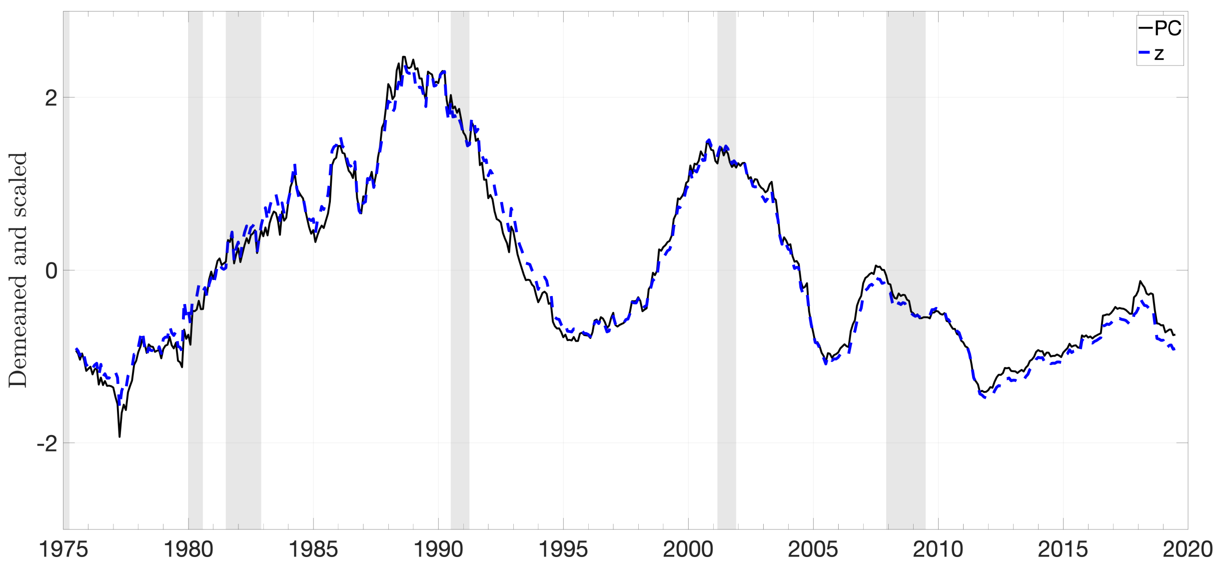

Figure 4: Default news index

The figure shows the fitted time series of the default news index z_t in (29), based on the data in Figure 3 and the parameter estimates in Table 1. It also displays the first principal component (PC) of the cohort-specific default news. The data are sourced from Moody's annual reports. Data for cohorts formed at the beginning of year t are shown in the figure as of time $t+2.5$. The shaded areas indicate NBER recessions.

Using the parameters in Panel B of Table 1, we compute default loss beta estimates according to (32). These beta estimates are depicted in Figure 5, in the form of $\log(-\beta_{L,jt})$ to represent the first component of excess credit spreads per unit of expected losses in (25). For investment-grade cohorts, we observe a moderate upward trend over time in the beta component of excess credit spreads, especially for Aa-rated firms and A-rated firms. For high-yield cohorts, on the other hand, the beta component is more volatile with a small downward trend.

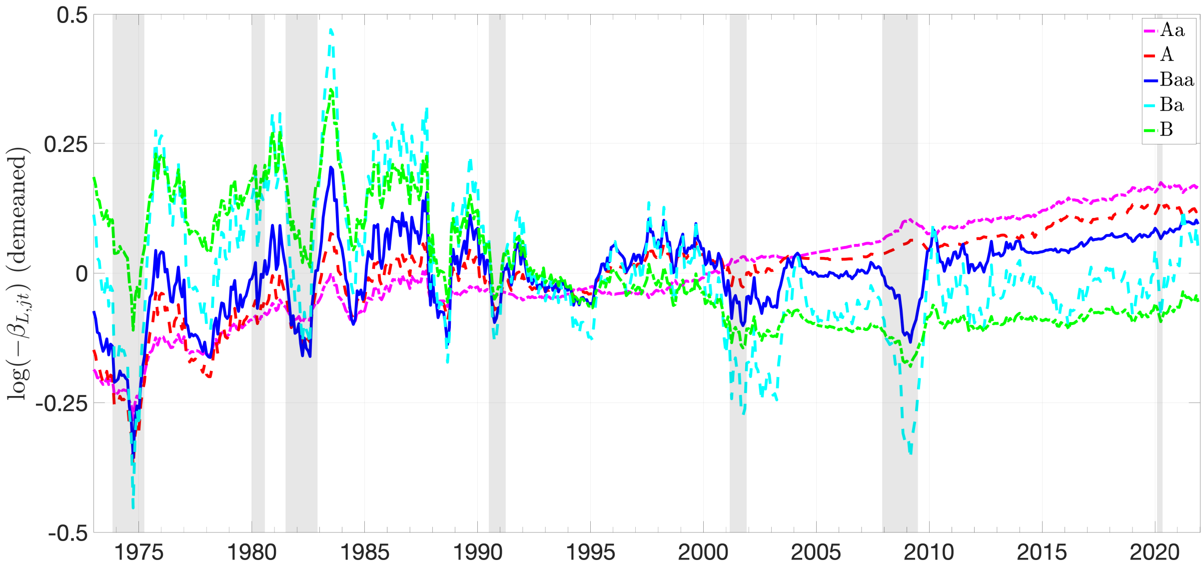

Figure 5: Default loss betas

The figure shows the monthly time series of $\log(-\beta_{L,jt})$, from January 1, 1973 to December 1, 2021, based on the data in Figure 3 and the parameter estimates in Table 1.

3. Measuring Time Variation in Risk Preferences

We take cohorts to be defined narrowly enough so that within-cohort firms have the same illiquidity mark-ups, $\ell_{it} = \ell_{j_{it}}$. Equation (25) then implies that $\widehat{\text{cs}}_{it} = \widehat{\text{cs}}_{j_{it}t}$, where $\widehat{\text{cs}}_{j_{it}t}$ is the within-cohort average credit spread. At the cohort level, (25) is equivalent to

$$\log\left(\frac{\widehat{\text{cs}}_{jt} - \mathbb{E}_t(L_{j,t+1})}{\mathbb{E}_t(L_{j,t+1})}\right) \quad = \quad \log(-\beta_{L,jt}) + \log(\text{prem}_t) + \ell_j. \qquad (37)$$

Having obtained estimates of default loss betas, we can now use them to estimate the risk premium x_t. Specifically, substituting (32) into (37) gives

$$\log\left(\frac{\widehat{\mathrm{cs}}_{jt} - \mathbb{E}_t(L_{j,t+1})}{K_{jt}}\right) \quad = \quad \log(\mathrm{prem}_t) + \ell_j. \tag{38}$$

which allows us to estimate $\log(\mathrm{prem}_t)$ as time fixed effects in a regression of the left-hand side in (38) on time and cohort fixed effects.

3A. Credit spread and expected loss data

The credit spreads s_{it} are obtained using month-end prices of senior unsecured debt issued by public non-financial U.S.-domiciled firms.[7] Prices of individual corporate bonds are collected from TRACE, the Lehman Brothers Fixed Income Database, and the Mergent FISD/NAIC Database (ordered by priority). In combination, these three sources span the period January 1973 to September 2021. We aggregate these data to the firm level by first calculating each bond's credit spread as the difference between the bond's yield and that of the maturity-matched Treasury.[8] The Treasury yield curve is constructed using the methodology in Gurkaynak, Sack, and Wright (2007) and the associated model parameter estimates provided by the Federal Reserve Board.[9] In a second step, the firm-level credit spread, s_{it}, is calculated as a weighted average of the firm's bond yield spreads where the weights are face values.[10] If the firm's credit spread is negative in any given month, we delete the observation from the sample. Likewise, we delete firm-month observations where the spread is far below that of other firms in the same rating category. We focus on medium-term credit spreads by restricting the computation of s_{it} to include only bonds with a remaining time to maturity between three and seven years.

[7]Public status is identified by matching bond issuers to CRSP/Compustat files. Bonds are matched with issuers using 6-digit historical cusips, or via the issuer family structure reported by Mergent FISD.

[8]The TRACE data are cleaned using the algorithm developed by Dick-Nielsen (2014). The Lehman and TRACE databases report yields, but the NAIC database only has prices. We compute NAIC yields using the information on maturity, coupon and early redemption features reported in Mergent FISD, and then choose the minimum of the yield to maturity and the yield to first call.

[9]Daily yield curve calibration results are available from https://www.federalreserve.gov/data/nominal-yield-curve.htm.

[10]The weights are face values rather than amounts outstanding. The latter are not reported in the Lehman data.

Because the original-issue high-yield market is in its infancy until the mid-1980s, there are few firms with ratings below Baa in the early years of the sample. This is especially true of Caa and lower rated bonds, which remain a small portion of the bond market throughout the sample period. To ensure that there are a sufficient number of firms available for estimating rating-specific default loss betas, we exclude all firms with ratings above Aa or below B. In addition, there are a few months in the 1970s when there are fewer than two high-yield firms in the sample, which prevents reliable estimation of the model. These months are dropped from the sample altogether. Firms with date for less than 12 months are excluded. This leaves us with 162,540 firm-month observations, covering 1,469 public non-financial U.S. firms over the period January 1973 to September 2021.

The range of credit quality in our data may be judged from Table B.1, which categorizes firms according to their median rating over the sample period. The table shows, for each letter rating, the number of firms in our study with that median rating. As the table indicates, the firms in our sample tend to be of medium to low credit quality. In the technology and utilities sectors, firms are rated investment-grade more often than high-yield, whereas energy and media firms tend to be rated high-yield. Capital and consumer industries account for over half of the sample. Summary statistics for excess credit spreads per unit of expected losses, $s_{jt}/\mathbb{E}_t(L_{j,t+1}) - 1$, are reported in Table B.2. As expected, credit spreads scaled by expected losses decrease as default risk increases, consistent with the literature on the credit spread puzzle. That is, the excess spread over and above expected losses is proportionately higher for investment-grade firms compared to high-yield firms (Eom, Helwege, and Huang, 2004; Huang and Huang, 2012; Berndt, 2015; Berndt, Douglas, Duffie, and Ferguson, 2018). Table B.3 presents additional descriptive statistics for the firms in our sample. By industry, technology firms tend to be the largest and utilities the smallest. Credit spreads tend to be higher for firms in the energy sector and lower, at the median, in consumer industries, technology and transportation.[11]

Figure 6 plots average credit spreads by letter rating for our sample. As expected, spreads

[11] While the number of investment-grade utilities in our sample exceeds that of high-yield utilities (Table B.1), there are more firm-month observations for riskier utilities. This explains the fairly high value in Table B.3 of median default probabilities for the utilities sector.

are highest for firms with the lowest credit rating. Credit spreads rise around recessions, before reverting back to lower levels.

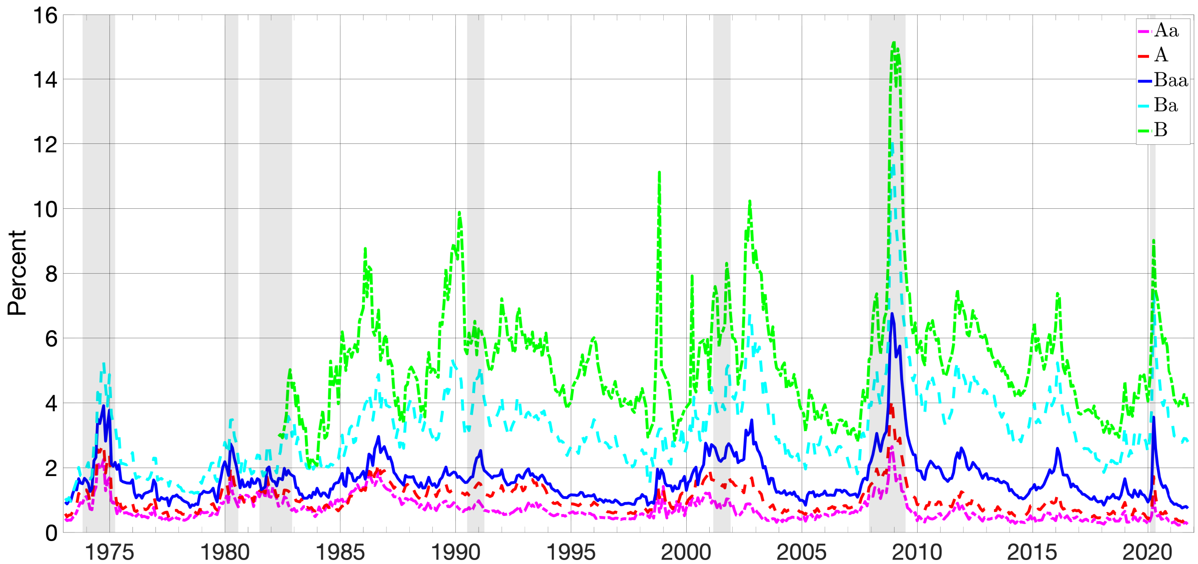

Figure 6: Credit spreads by letter rating

The figure shows the monthly times series of average five-year senior unsecured bond yield spreads by Moody's letter rating. The sample includes 1,469 public non-financial US firms over the period January 1973 to September 2021.

To estimate expected default losses betas we require data on actual defaults, which we obtain from the Moody's Default and Recovery Database. We also require data on recovery rates. We use a recovery rate of 0.39, 0.46, 0.44, 0.42 and 0.37 for Aa, A, Baa, Ba and B rated firms, respectively, to reflect the average recovery rates for senior unsecured bonds measured by trading prices reported in Moody's Investors Service (2022) as of 2.5 years prior to default, for the period 1983–2021.

3B. Estimation results

We estimate $\log(\text{prem}_t)$ as time fixed effects in a regression of the left-hand side in (38) on time and cohort fixed effects. Panel A of Table 2 shows the results of this regression, including the coefficients on the cohort fixed effects for each of the rating categories (the omitted category is Baa). We find that illiquidity mark-ups of bond risk premia, ℓ_j, are significantly larger for investment-grade firms than for high-yield firms.

We plot the time series of $\log(\text{prem}_t)$ in Figure 7. The market risk premium is higher in recessions than other periods, with the highest value of $\log(\text{prem}_t)$ occurring in the GFC. Another

Table 2: Risk premium identification

	constant	Aa	A	Ba	B	R-sqr	RMSE	Obs
Est	-4.303^{**}	1.322^{**}	0.489^{**}	-1.091^{**}	-1.561^{**}	0.959	0.256	2,793
SE	(0.217)	(0.015)	(0.011)	(0.014)	(0.015)			

This table reports the results for the panel-data regression (38) which identifies $\log(x_t)$ as month fixed effects in a regression of $\log([\widehat{\text{cs}}_{jt} - \mathbb{E}_t(L_{j,t+1})]/K_{jt})$ on month and cohort fixed effects. The benchmark cohort is Baa, and the benchmark month is September 2021. Robust standard errors are shown in parentheses. The sample covers 1,469 public non-financial US firms over January 1973 to September 2021.

spike occurs in the Covid recession, but the magnitude in that period is not very different from the 1975 recession. The risk premium is lowest in boom periods, especially in the late 1970s, late 1990s, and mid 2000s. The lowest level occurs a few years before Covid, around the time the Federal Reserve begins to raise off of the zero lower bound.

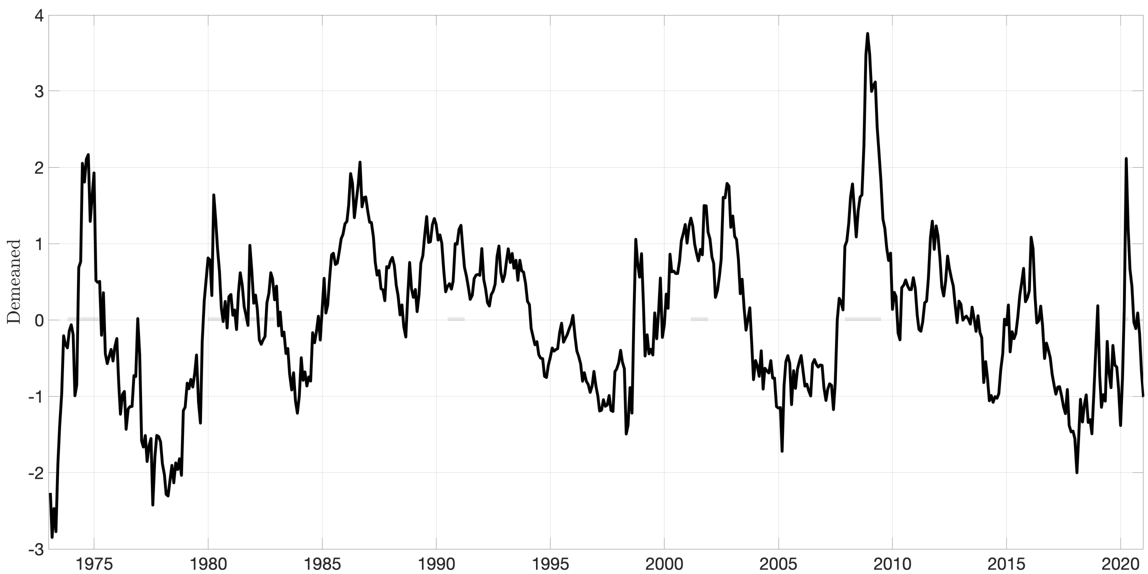

Figure 7: Market risk premium

The figure shows the monthly times of $\log(\text{prem}_t)$, from January 1975 to September 2021.

Figure B.1 compares our $\log(\text{prem}_t)$ measure to alternative risk premium proxies. It shows that measured risk premia track the excess bond premium of Gilchrist and Zakrajšek (2012), the Baa-Aaa spread, the Bekaert, Engstrom, and Xu (2021) risk aversion measure, and the VIX index reasonably well.

3C. Moment conditions

Our main focus is on a robust calibration of the relationship (3). While we cannot observe s_t directly, Equation (21) states that s_t is approximately equal to $-\log(\text{prem}_t)$, at least when the log surplus consumptions ratio is close to its steady state $\bar{s}$. So, we train the persistence parameter θ_0 to the measured autocorrelation of $\log(\text{prem})$, and θ_1 and θ_2 to the correlation between $\log(\text{prem}_{t+1})$ and x_t and the correlation between $\log(\text{prem}_{t+1})$ and x_{t-1}, respectively. By fitting the model to match these three parameter estimates, we are able to generate estimates of the relationship between monetary policy shocks and output.

The corresponding empirical moment conditions are summarized in Table 3,along with the other parameters used in the model. The table reports statistics for the period 1994.I–2019.I, which matches the time period in Pflueger and Rinaldi (2022). The measured autocorrelation of $\log(\text{prem})$ is 0.83, its correlation with the lagged log output gap is -0.13, and its correlation with the twice lagged output gap is 0.02.

Figure B.2 shows the quarterly time series of these moments. For each month, the moments are computed using data for the past 40 quarters. The autocorrelation of the log risk premium remains fairly flat throughout the sample period, hovering around 0.8, until the Covid pandemic when it drops to below 0.6. The correlation between the log risk premium and the lagged output gap is consistently lower for the once-lagged output gap than for the twice-lagged output gap. It is negative on average for the once-lagged output gap, and positive for the twice-lagged output gap. Both types of correlation were highest between 1990–1995, and lowest in the lead-up to the Covid pandemic.

Table 3: Parameters

Panel A: Calibrated parameters		Value	Source and empirical target
Preferences			
Consumption growth	g	1.89	Avg consumption growth Campbell and Cochrane (1999)
Utility curvature	γ	2	Equity Sharpe ratio Campbell and Cochrane (1999)
Steady-state risk-free rate	$\bar{r}$	0.94	Avg real risk-free rate Campbell and Cochrane (1999)
Monetary policy			
MP coeff output	γ_x	1.5	Reduced-form regression Taylor (1993)
MP coeff inflation	γ_π	0.5	Reduced-form regression Taylor (1993)
MP persistence	ρ_i	0.80	Reduced-form regression Clarida, Gali, and Gertler (2000)
Inflation			
PC backward coeff	ρ_π	0.80	Qtrly inflation persistence Fuhrer (1997)
PC slope	κ	0.0062	Regional inflation-unemployment slope Hazell et al. (2022)
Consumption			
Consumption–output gap link	ϕ	0.93	Corr(output gap, detrended consump.) Campbell, Pflueger, and Viceira (2020)

Panel B: Estimated parameters		Empirical target
SD quarterly MP shock (%)	σ_{MP}	SD annual cons. growth $\sigma_c = 1.5\%$
SD real rate (%)	Θ	SD annual real rate $\sigma_r = 1.35\%$
Persistence surplus consumption	θ_0	$\text{Corr}(\log(\text{prem}_{t+1}), \log(\text{prem}_t)) = 0.831$
Preference-lagged output gap links	θ_1	$\text{Corr}(\log(\text{prem}_{t+1}), x_t) = -0.126$
	θ_2	$\text{Corr}(\log(\text{prem}_{t+1}), x_{t-1}) = 0.016$

Panel A reports model parameter values, the articles that the parameter values are drawn from, and the moment in the data that the literature has targeted with this parameter. Consumption growth and the steady-state risk-free rate are in annualized percent. The monetary policy coefficient and the Phillips curve slope are in units corresponding to the empirical variables: the log output gap is in percent and the Fed Funds rate and inflation are in annualized percent. Panel B reports moments for the time series of log risk premia displayed in Figure 7. The third column in Panel B describes the moment that is matched by our calibration. The persistence of surplus consumption is annualized. The sample period for computing log(prem) moments is 1994.I–2019.I, to match the time period in Pflueger and Rinaldi (2022).

4. Preference Dynamics and Macroeconomic Fundamentals

This section calibrates the model in Section 1 to the moments in Table 3. The vector of parameters to be fitted is

$$\Theta = (\sigma_{MP}, \theta_0, \theta_1, \theta_2) \tag{39}$$

or, equivalently, $(\sigma_{MP}, \theta_0, \theta_1, \alpha)$.[12] For each (θ_1, α), we choose σ_{MP} and θ_0 to match the model-implied annualized consumption volatility to its target value of 1.5% and the autocorrelation of the log market risk premium to its target value of 0.83.

4A. Model-implied moments

We follow Campbell, Pflueger, and Viceira (2020) and simulate a draw of length $T = 10,000$, discarding the first 100 simulation periods to ensure that the system has reached the stochastic steady-state. Model moments are computed by averaging across two independent simulations.

4B. Fitted parameters

Figure 8 shows the fitted values for σ_{MP} and θ_0, for various combinations of θ_1 and α. The left side of the figure shows that the volatility of monetary policy (and therefore of consumption) is quite sensitive to the choice of α despite the fact that all of the plotted lines have a value of α that is close to one. On the right side, the choice of α has a larger impact as the value of θ_1 falls below -0.5 and is quite noticeable below -1. In contrast, as θ_1 approaches zero the sum of the backward-looking and forward-looking parameters becomes irrelevant, as the model collapses to that of Campbell and Cochrane (1999).

Figure 9 visualizes the corresponding model-implied moments for the preference-output gap links, together with their empirical counterparts. The left panel of the figure shows that there are parameter vectors $(\sigma_{MP}, \theta_0, \theta_1, \alpha)$ that simultaneously match consumption volatility, the persistence of the log risk premium, and the correlation between log risk premium and the lagged output gap. The right panel of the figure reveals that these parameter combinations tend to underestimate the correlation between log risk premium and the twice-lagged output gap, albeit only by a small amount.

Figure 9 points to values for α slightly greater than one, and to θ_1 values below minus one. To more formally choose among (θ_1, α) pairs, the left panel of Figure B.3 plots, for various values

[12] Recall that for a given θ_1 and α, θ_2 can be computed from (11).

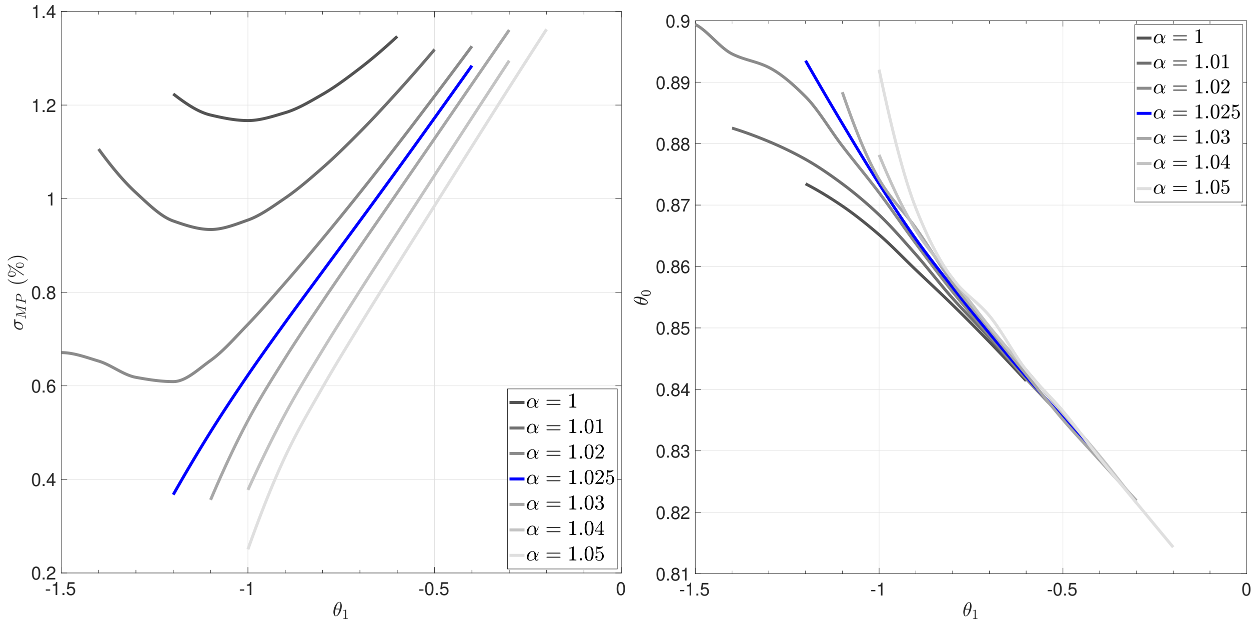

Figure 8: Fitted parameters σ_{MP} and θ_0

The figure shows the fitted values for σ_{MP} and θ_0, for various combinations of θ_1 and α. For each (θ_1, α), we choose σ_{MP} and θ_0 to match the model-implied annualized consumption volatility to its target value of 1.5% and the autocorrelation of the log market risk premium to its target value of 0.83 (Table 3). Only θ_1 values for which the model-implied standard deviations of real rates is between $\pm 1\%$ of its empirical target of 1.35% are shown.

of α, the value for θ_1 at which the model-implied and observed valued for $\text{corr}(\log(\text{prem}_{t+1}), x_t)$ match.[13] The right panel shows the corresponding absolute fitting error for $\text{corr}(\log(\text{prem}_{t+1}), \log(\text{prem}_{t-1}))$. The figure shows that this error is minimized at $\alpha = 1.025$, and that the associated best choice for θ_1 is -1.186.

Panel A of Table 4 reports the estimated parameter estimates. For $\alpha = 1.025$ and $\theta_1 = -1.186$, the values for σ_{MP} and θ_0 that match the model-implied annualized consumption volatility and the autocorrelation of the log market risk premium to their empirical targets are $\sigma_{MP} = 0.387$ and $\theta_0 = 0.892$. While the estimated persistence parameter θ_0 is close to the 0.87 estimate of Campbell and Cochrane (1999) that is used in many related studies, including Pflueger and Rinaldi (2022), our estimate for the standard deviation of monetary policy shocks σ_{MP} is lower than that reported in Pflueger and Rinaldi (2022). The difference in σ_{MP} estimates results from the restriction imposed by Pflueger and Rinaldi (2022) that the forward- and backward-looking terms in the Euler

[13] Recall that for each (θ_1, α), we choose σ_{MP} and θ_0 to match the model-implied annualized consumption volatility to its target value of 1.5% and the autocorrelation of the log market risk premium to its target value of 0.83 (Table 3).

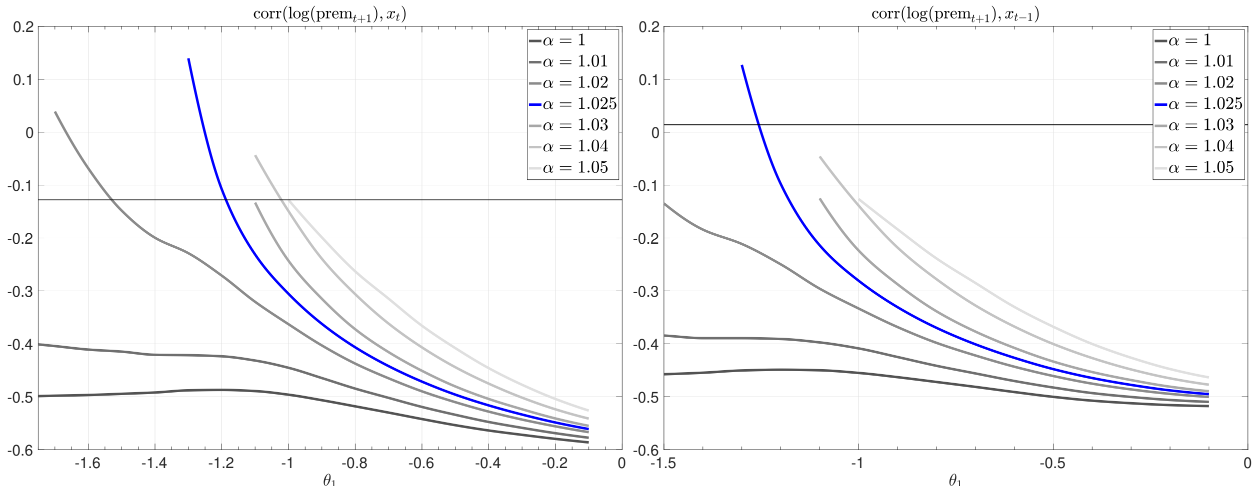

Figure 9: Model-implied versus empirical moments

The figure shows model-implied moments for log risk premia, for various values of $\alpha = f_x + \rho_x$. For each (θ_1, α), we choose σ_{MP} and θ_0 to match the model-implied annualized consumption volatility to its target value of 1.5% and the autocorrelation of the log market risk premium to its target value of 0.83 (Table 3). Only θ_1 values for which the model-implied standard deviations of real rates is between $\pm 1\%$ of its empirical target of 1.35% are shown. In the left panel, the black solid line correspond to the empirical target for Corr$(\log(\text{prem}_{t+1}), \log(\text{prem}_t))$ reported in Table 3 for the period 1994.I–2019.I, and in the right panel it corresponds to the empirical target for Corr$(\log(\text{prem}_{t+1}), \log(\text{prem}_{t-1}))$.

equation (10) add up to one, which places a constraint on consumption volatility at a given level of interest rate uncertainty. Figure 9 shows, however, that the restriction on the Euler equation does not draw much empirical support. We therefore allow the sum of the forward- and backward-looking terms in (10) to differ from one. This enables the model to match to the target correlation between surplus consumption and the output gap. At the same time, it implies a higher consumption volatility for a given level of interest rate volatility, meaning that target consumption volatility is matched at a lower value for σ_{MP}.

The calibrated preference parameters imply an annualized discount factor of 0.979 and an Euler equation with roughly equal-sized forward- and backward-looking coefficients ($f_x = 0.552, \rho_x = 0.473$). The sum of these two coefficients is 1.025, so slightly larger than in Pflueger and Rinaldi (2022) ($\alpha = 1$) but smaller than in Campbell, Pflueger, and Viceira (2020) ($\alpha = 1.04$). The coefficient on the real interest rate in the Euler equation is 0.236, which is in line with the estimate in Yogo (2004) of 0.2.

The model implies that the trough output response occurs 9–10 quarters after the initial monetary policy shock, and measures around 2.2% for every 100 basis point increase in the Fed funds

Table 4: Estimated and implied parameters

		Value
Panel A: Estimated parameters		
Std. Quarterly MP Shock (%)	σ_{MP}	0.387
Surplus Consumption - Persistence	θ_0	0.892
Surplus Consumption - Output Gap	θ_1	-1.186
Sum of forward- and backward looking terms in Euler equation	α	1.025
Panel B: Implied parameters		
Discount factor	β	0.979
Steady-state surplus consumption ratio	$\overline{S}$	0.014
Maximum surplus consumption ratio	S_{max}	0.023
Euler equation forward coefficient	f_x	0.473
Euler equation backward coefficient	ρ_x	0.552
Euler equation real rate slope	ψ	0.236
Surplus consumption–Lagged output gap	θ_2	1.169
Panel C: Implied macroeconomic dynamics		
SD annual consumption growth	σ_c	1.5
SD annual change Fed Funds rate	σ_r	1.0
Trough effect consumption (%)		-2.2
Lag trough (quarters)		9–10
Trough effect output gap (%)		-1.6
Lag trough (quarters)		7

This table reports the results for the parameter calibration.

rate. These estimates fall within those of Christiano, Eichenbaum, and Evans (1999) who report a reduction in output by 70 basis points at eight quarters and Romer and Romer (2004) who report a reduction by 4.3% at eight quarters, except that our trough lag estimate is slightly longer than theirs.

The top panel of Figure 10 depicts the transmission of a monetary policy shock. A positive shock leads to an increase in the short-term risk-free rate that mean-reverts and converges back to zero at about five quarters.The output gap initially declines and reaches a trough response of around -1.6 percentage points around nine to ten quarters, before converging back to its steady-state value. Inflation responds more slowly than the output gap and shows a moderate negative response.

The bottom panel of Figure 10 reproduces the corresponding results of Pflueger and Rinaldi (2022). Relative to their approach, our calibration of the relationship between preferences and the

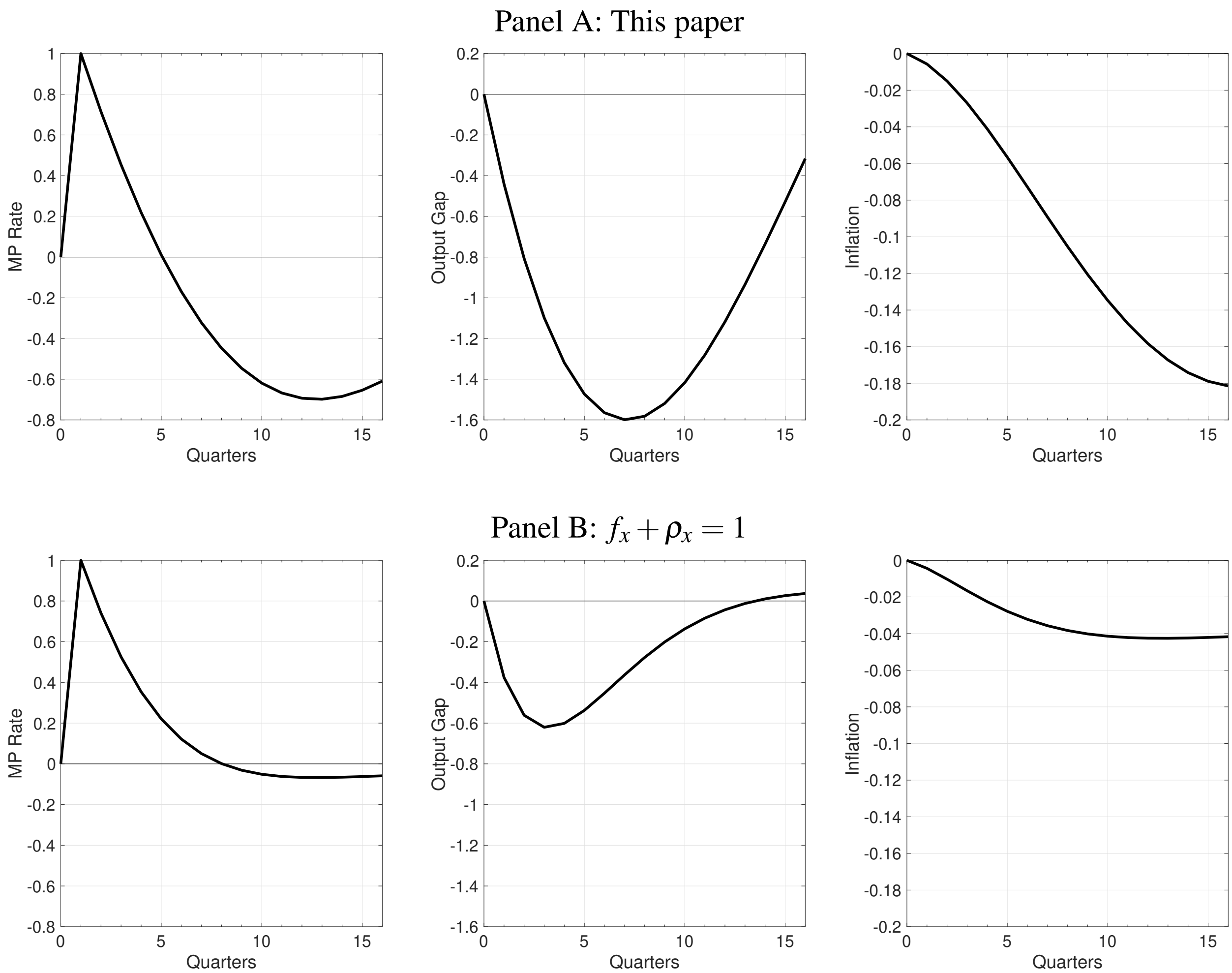

Figure 10: Model-implied impulse responses to monetary policy shock

The figure shows the model-implied impulse responses to a 100 basis point monetary policy shock. The left panel shows the response of the federal funds rate in annualized percent, the middle panel shows the response of the output gap in percent, and the right panel shows the response of inflation in annualized percent. The figures shows results for our model fit (Panel A), and under the restriction $\alpha = 1$ (Panel B).

output gap in (3) implies a more pronounced and longer-lasting hump in the response of output to monetary policy shocks.

5. Concluding Remarks

We present empirical evidence on the relationship between surplus consumption and the lagged output gap using a novel method of extracting a measure of the market risk premium from corporate bond prices. Our risk premium measure is closely related to the risk sensitivity variable in habit-formation utility models based on Campbell and Cochrane (1999), which allows us to estimate the correlation with the output gap in a macroeconomic model.

Our evidence is particularly relevant for testing the assumptions in recent macroeconomic models that relate FOMC policy to the output gap. For example, the framework in Campbell, Pflueger, and Viceira (2020) assumes that surplus consumption is a function of the lagged output gap and the twice-lagged output gap, as well as of its own lag. Such an assumption has the appealing quality of inducing a hump shape in the impulse response function of output to a monetary policy shock. We provide empirical evidence that the lagged output gap enters the surplus consumption equation, validating the assumption in these recent models.

While our results provide support for this type of preference specification, we note that the forward and backward looking weights in the Euler equation must be flexible if the moments of the log risk premium are to be matched. We find that setting the sum of the weights to one leads to a worse fit of the model compared to a sum that is slightly higher (1.025 in our estimation).

Having calibrated the model to the risk premium moments, we are able to use the estimates of the lagged output gap coefficients to generate impulse response functions. We find that the calibration estimates are consistent with a dynamic macroeconomic model where a 100 basis point Fed funds shock leads to a drop in output of 2.2%. The impulse response function associated with this set of parameters has the desired hump shape with a trough at nine to ten quarters. This places our estimates of the impact of monetary policy in output between those of Christiano, Eichenbaum, and Evans (1999) and Romer and Romer (2004).

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APPENDIX

A. Model Derivations and Macroeconomic Dynamics

This appendix provides detailed derivations for the results in Section 1.

A.1. Euler equation

Substituting (2), (3) and (4) into (8), and simplifying, gives

$$
\begin{aligned}
r_t &= -\log[\mathbb{E}_t(\exp(-\gamma(\Delta c_{t+1}+\Delta s_{t+1})))] && \text{(A.1)}\\
&= -\log(\exp(-\gamma\,\mathbb{E}_t(\Delta c_{t+1}+\Delta s_{t+1})+\frac{1}{2}\gamma^2(1+\lambda_{t-1})^2\sigma_c^2)) && \text{(A.2)}\\
&= \gamma\,\mathbb{E}_t(\Delta c_{t+1})+\gamma\mathbb{E}_t(\Delta s_{t+1})-\frac{1}{2}\gamma^2(1+\lambda_t)^2\sigma_c^2 && \text{(A.3)}\\
&= \gamma\,\mathbb{E}_t(\Delta c_{t+1})-\gamma(1-\theta_0)(s_t-\bar{s}_t)+\gamma\theta_1 x_t+\gamma\theta_2 x_{t-1} && \text{(A.4)}\\
&\quad +\gamma\theta_3\,\mathbb{E}_t(x_{t+1})-\frac{1}{2}\gamma^2(1+\lambda(s_t))^2\sigma_c^2 && \text{(A.5)}\\
&= \gamma\,\mathbb{E}_t(\Delta c_{t+1})+\gamma\theta_1 x_t+\gamma\theta_2 x_{t-1}+\gamma\theta_3\,\mathbb{E}_t(x_{t+1}). && \text{(A.6)}
\end{aligned}
$$

The last equation holds because the sensitivity function $\lambda(s_t)$ has just the right form so that s_t drops out.

Substituting (6) into (A.6), and rearranging, yields

$$
\begin{aligned}
r_t &= \gamma\mathbb{E}_t(x_{t+1})-\gamma\phi x_t+\gamma\theta_1 x_t+\gamma\theta_2 x_{t-1}+\gamma\theta_3\,\mathbb{E}_t(x_{t+1}) && \text{(A.7)}\\
r_t &= \gamma\mathbb{E}_t(x_{t+1})-\gamma(\phi-\theta_1)x_t+\gamma\theta_2 x_{t-1}+\gamma\theta_3\,\mathbb{E}_t(x_{t+1}) && \text{(A.8)}\\
\gamma(\phi-\theta_1)x_t &= \gamma(1+\theta_3)\,\mathbb{E}_t(x_{t+1})+\gamma\theta_2 x_{t-1}-r_t && \text{(A.9)}\\
x_t &= \frac{1+\theta_3}{\phi-\theta_1}\mathbb{E}_t(x_{t+1})+\frac{\theta_2}{\phi-\theta_1}x_{t-1}-\frac{1}{\gamma(\phi-\theta_1)}r_t. && \text{(A.10)}
\end{aligned}
$$

A.2. Macroeconomic dynamics

The macroeconomic dynamics are described by (10), (12) and (13). They can be expressed as

$$0 = F\,\mathbb{E}_t(Y_{t+1}) + GY_t + HY_{t-1} + M\varepsilon_t, \tag{A.11}$$

where $F = \begin{bmatrix} f_x & \psi & 0 \\ 0 & f_\pi & 0 \\ 0 & 0 & 0 \end{bmatrix}$, $G = \begin{bmatrix} -1 & 0 & -\psi \\ \kappa & -1 & 0 \\ (1-\rho_i)\psi_x & (1-\rho_i)\psi_\pi & -1 \end{bmatrix}$, $H = \begin{bmatrix} \rho_x & 0 & 0 \\ 0 & \rho_\pi & 0 \\ 0 & 0 & \rho_i \end{bmatrix}$, and $M = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$.

A.3. Derivation of $\mathrm{prem}_{Y+V_Y,t} = \beta_{Y,t}\,\mathrm{prem}_t$

The tower property of conditional expectations gives

$$\begin{aligned}
V_{Y,t} &= \sum_{j=1}^{\infty} \mathbb{E}_t(\exp(\sum_{s=1}^{j} \Delta m_{t+s})Y_{t+j}), && \text{(A.12)}\\
&= \mathbb{E}_t(\exp(\Delta m_{t+1}))\,\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})\frac{\mathbb{E}_t(\exp(\Delta m_{t+1})(Y_{t+1}+V_{Y,t+1}))}{\mathbb{E}_t(\exp(\Delta m_{t+1}))\,\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})} && \text{(A.13)}\\
&= \mathbb{E}_t(\exp(\Delta m_{t+1}))\,\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})\left(1+\mathrm{Cov}_t\left(\frac{\exp(\Delta m_{t+1})}{\mathbb{E}_t(\exp(\Delta m_{t+1}))}, \frac{Y_{t+1}+V_{Y,t+1}}{\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})}\right)\right) && \text{(A.14)}\\
&= \mathbb{E}_t(\exp(\Delta m_{t+1}))\,\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})(1-\mathrm{prem}_{Y+V_Y,t}), && \text{(A.15)}
\end{aligned}$$

where $\mathrm{prem}_{Y+V_Y,t}$ is defined as

$$\mathrm{prem}_{Y+V_Y,t} = -\mathrm{Cov}_t\left(\frac{\exp(\Delta m_{t+1})}{\mathbb{E}_t(\exp(\Delta m_{t+1}))}, \frac{Y_{t+1}+V_{Y,t+1}}{\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})}\right). \tag{A.16}$$

Let $R_{Y,t+1} = \frac{Y_{t+1}+V_{Y,t+1}}{V_{Y,t}}$ denote the one-period gross return on Y, and $R_{f,t} = 1/\mathbb{E}_t(\exp(\Delta m_{t+1}))$ is the one-period gross return on the risk-free asset. Then,

$$\mathbb{E}_t(R_{Y,t+1}) - R_{f,t} = \frac{\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})}{V_{Y,t}} - \frac{1}{\mathbb{E}_t(\exp(\Delta m_{t+1}))} \tag{A.17}$$

$$= \frac{\mathbb{E}_t(\exp(\Delta m_{t+1}))\,\mathbb{E}_t(Y_{t+1}+V_{Y,t+1}) - V_{Y,t}}{V_{Y,t}\,\mathbb{E}_t(\exp(\Delta m_{t+1}))} \tag{A.18}$$

$$= -\frac{\mathbb{E}_t(\exp(\Delta m_{t+1}))\,\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})\mathrm{Cov}_t\left(\frac{\exp(\Delta m_{t+1})}{\mathbb{E}_t(\exp(\Delta m_{t+1}))}, \frac{Y_{t+1}+V_{Y,t+1}}{\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})}\right)}{V_{Y,t}\,\mathbb{E}_t(\exp(\Delta m_{t+1}))} \tag{A.19}$$

and thus

$$\frac{\mathbb{E}_t(R_{Y,t+1}) - R_{f,t}}{\mathbb{E}_t(R_{Y,t+1})} = -\mathrm{Cov}_t\left(\frac{\exp(\Delta m_{t+1})}{\mathbb{E}_t(\exp(\Delta m_{t+1}))}, \frac{Y_{t+1}+V_{Y,t+1}}{\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})}\right). \tag{A.20}$$

Equating (A.16) and (A.20) yields

$$\mathrm{prem}_{Y+V_Y,t} = \frac{\mathbb{E}_t(R_{Y,t+1}) - R_{f,t}}{\mathbb{E}_t(R_{Y,t+1})} \tag{A.21}$$

$$\approx 1 - \exp\left(-(\log(\mathbb{E}_t(R_{Y,t+1})) - r_{f,t})\right) \tag{A.22}$$

$$\approx \log(\mathbb{E}_t(R_{Y,t+1})) - r_{f,t}. \tag{A.23}$$

Using (2), and the equilibrium outcome where Δm_{t+1} is conditionally normally distributed with mean $\mathbb{E}_t(-\gamma(\Delta c_{t+1}+\Delta s_{t+1}))$ and variance $\frac{1}{2}\gamma^2(1+\lambda(s_t))^2\sigma_c^2$, we obtain

$$\frac{\exp(\Delta m_{t+1})}{\mathbb{E}_t(\exp(\Delta m_{t+1}))} = \frac{\exp(-\gamma(\Delta c_{t+1}+\Delta s_{t+1}))}{\mathbb{E}_t(\exp(-\gamma(\Delta c_{t+1}+\Delta s_{t+1})))} \tag{A.24}$$

$$= \exp\left(-\gamma(1+\lambda(s_t))\varepsilon_{c,t+1} - \frac{1}{2}\gamma^2(1+\lambda(s_t))^2\sigma_c^2\right) \tag{A.25}$$

$$\approx 1 - \gamma(1+\lambda(s_t))\varepsilon_{c,t+1} - \frac{1}{2}\gamma^2(1+\lambda(s_t))^2\sigma_c^2. \tag{A.26}$$

Substituting (A.26) into (A.16) yields the approximate relationship

$$\text{prem}_{Y+V_Y,t} \approx \underbrace{\frac{\text{Cov}_t\left(\varepsilon_{c,t+1}, \frac{Y_{t+1}+V_{Y,t+1}}{\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})}\right)}{\sigma_c^2}}_{=\beta_{Y,t}} \underbrace{\gamma(1+\lambda(s_t))\sigma_c^2}_{=\text{prem}_t}. \tag{A.27}$$

For cases where $Y_{t+1}+V_{Y,t+1}$ has a conditional log-normal distribution close to one, including the one-period consumption claim where $Y_{t+1}+V_{Y,t+1}=C_{t+1}$,

$$\beta_{Y,t} \approx \frac{\text{Cov}_t\left(\varepsilon_{c,t+1}, \varepsilon_{\log(Y+V_Y),t+1}\right)}{\sigma_c^2}. \tag{A.28}$$

Substituting (4) into (20), and considering cases where s_t is close to the steady state, we obtain

$$\text{prem}_t = \gamma\frac{1}{\overline{S}}\sqrt{1-2(s_t-\overline{s})}\sigma_c^2 \tag{A.29}$$

$$\log(\text{prem}_t) = \text{constant} + \frac{1}{2}\log(1-2(s_t-\overline{s})) \tag{A.30}$$

$$\approx \text{constant} + \frac{1}{2}\log[\exp(-2(s_t-\overline{s}))] \tag{A.31}$$

$$= \text{constant} - s_t. \tag{A.32}$$

A.4. Corporate bond pricing

We aim to express the real bond price as $B_{it} = \mathbb{E}_t(\exp(\Delta m_{t+1}))(1-s_{it})$. Since

$$B_{it} = \mathbb{E}_t(\exp(\Delta m_{t+1})(1-L_{i,t+1})) \tag{A.33}$$

$$= \mathbb{E}_t(\exp(\Delta m_{t+1}))\mathbb{E}_t(1-L_{i,t+1})\frac{\mathbb{E}_t(\exp(\Delta m_{t+1})(1-L_{i,t+1}))}{\mathbb{E}_t(\exp(\Delta m_{t+1}))\mathbb{E}_t(1-L_{i,t+1})} \tag{A.34}$$

$$= \mathbb{E}_t(\exp(\Delta m_{t+1}))\mathbb{E}_t(1-L_{i,t+1})(1-\text{prem}_{1-L,it}), \tag{A.35}$$

we obtain

$$s_{it} = \mathbb{E}_t(L_{i,t+1}) + \mathbb{E}_t(1-L_{i,t+1})\text{prem}_{1-L,it}. \tag{A.36}$$

Observed credit spreads in excess of expected may reflect compensation for illiquidity risk,

$$\widehat{s}_{it} - \mathbb{E}_t(L_{i,t+1}) \quad = \quad \mathbb{E}_t(1 - L_{i,t+1})\,\text{prem}_{1-L,it}\,\ell_{it}, \tag{A.37}$$

as modeled by ℓ_{it}. Applying the definitions (18) and (A.16), Equation (A.37) implies

$$\frac{\widehat{s}_{it} - \mathbb{E}_t(L_{i,t+1})}{\mathbb{E}_t(L_{i,t+1})} \quad = \quad \frac{\mathbb{E}_t(1 - L_{i,t+1})}{\mathbb{E}_t(L_{i,t+1})}\,\beta_{1-L,it}\,\text{prem}_t\,\ell_{it} \tag{A.38}$$

$$= \quad -\frac{\mathbb{E}_t(1 - L_{i,t+1})}{\mathbb{E}_t(L_{i,t+1})}\,\text{Cov}_t\left(\frac{\exp(\Delta m_{t+1})}{\mathbb{E}_t(\exp(\Delta m_{t+1}))}, \frac{1 - L_{i,t+1}}{\mathbb{E}_t(1 - L_{i,t+1})}\right)\text{prem}_t\,\ell_{it} \tag{A.39}$$

$$= \quad \text{Cov}_t\left(\frac{\exp(\Delta m_{t+1})}{\mathbb{E}_t(\exp(\Delta m_{t+1}))}, \frac{L_{i,t+1}}{\mathbb{E}_t(L_{i,t+1})}\right)\text{prem}_t\,\ell_{it} \tag{A.40}$$

$$= \quad -\beta_{L,it}\,\text{prem}_t\,\ell_{it}. \tag{A.41}$$

B. Additional Tables and Figures

Table B.1: Distribution of firms across industries and by credit quality

	Aa	A	Baa	Ba	B	All
Capital Industries	5	63	102	85	120	375
Consumer Industries	12	49	83	60	89	293
Energy & Environment	4	21	57	45	88	215
Media & Publishing	2	13	25	16	25	81
Retail & Distribution	1	20	44	31	21	117
Technology	6	46	69	40	50	211
Transportation	1	2	16	7	10	36
Utilities	4	52	68	11	2	137
Other	1	0	2	1	0	4
All	36	266	466	296	405	1,469

The table reports the distribution of firms across industries and by median Moody's senior unsecured issuer-level rating. The sample includes 1,469 public non-financial US firms, over the period January 1973 to September 2021.

Table B.2: Credit risk premia across industries and by credit quality

	Aaa	Aa	A	Baa	Ba	B
Capital Industries	4.12	3.63	2.58	1.68	0.53	−0.56
Consumer Industries	3.29	2.95	2.28	1.48	0.35	−0.86
Energy & Environment	3.52	3.32	2.63	1.70	0.57	−0.44
Media & Publishing	–	2.41	2.69	1.55	0.72	−0.62
Retail & Distribution	3.96	2.81	2.57	1.54	0.40	−0.45
Technology	3.80	2.94	2.39	1.69	0.52	−0.58
Transportation	–	2.53	2.99	1.39	0.34	−0.48
Utilities	5.32	–	3.55	1.38	−0.03	−1.47

The table reports the median log credit risk premium, $x_{it} = \log(S_{it} - P_{it}L_i) - \log(P_{it}L_i)$, across industries and by Moody's senior unsecured issuer-level rating. The sample includes 1,276 public non-financial U.S. firms, over the period August 1974 to September 2020.

Table B.3: Firm characteristics by industry

	Capital Ind	Cons Ind	Energy/ Envmt	Media/ Publ	Retail/ Distr	Tech	Trans-port	Utilities
Market capitalization	2,543	6,077	4,255	2,788	6,466	8,656	4,042	1,592
Total assets	4,228	6,213	7,433	4,272	7,914	9,700	9,470	2,654
Book value of debt	2,089	3,052	3,304	2,155	4,593	4,544	4,709	1,554
Market-to-book ratio	0.77	1.03	0.76	0.75	0.86	0.85	0.72	0.66
(Cash+ST invt)/assets	0.05	0.05	0.03	0.03	0.03	0.07	0.04	0.01
Return on assets	0.04	0.07	0.04	0.04	0.05	0.05	0.04	0.03
Operating margin	0.09	0.14	0.10	0.14	0.05	0.12	0.10	0.23
Dividends	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.02
Debt issuance	0.01	0.02	0.02	0.00	0.03	0.02	0.02	0.02
Equity issuance	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.01
Interest coverage	0.00	0.00	3.96	0.00	0.00	0.00	0.00	3.05
Leverage	0.48	0.50	0.44	0.50	0.57	0.48	0.47	0.53
Trailg 12mo equity return	0.05	0.08	0.01	0.06	0.06	0.07	0.08	0.12
Trailg 12mo SSR	0.09	0.06	0.11	0.09	0.08	0.07	0.09	0.07
5yr credit spread	179	120	203	179	139	125	130	167
10yr credit spread	150	112	163	154	127	120	110	189
5yr PD	42	29	56	43	37	26	37	112
10yr PD	52	29	66	56	39	26	39	146
Years in sample	8	7	5	5	6	5	7	3

The table reports median firm characteristics by industry. Market capitalization, total assets and book value of debt are reported in millions of U.S. dollars. Book debt is computed as the sum of short-term debt and long-term debt. The return on assets is calculated as net income scaled by assets. Operating margin is computed as operating income scaled by sales. Dividends are annual cash dividends scaled by total assets. Debt issuance is the annual change in book debt scaled by lagged assets. Equity issuance is the annual growth of balance sheet equity, net of retained earnings, scaled by lagged assets. Interest coverage is EBITDA divided by annual interest expense. Leverage is book debt divided by total assets. The trailing equity returns and trailing sum of squared equity returns (SSR) are computed using daily data for the past 12 months. Credit spreads and default probabilities (PDs) are annualized and reported in basis points. The sample includes 1,276 public non-financial U.S. firms, over the period August 1974 to September 2020.

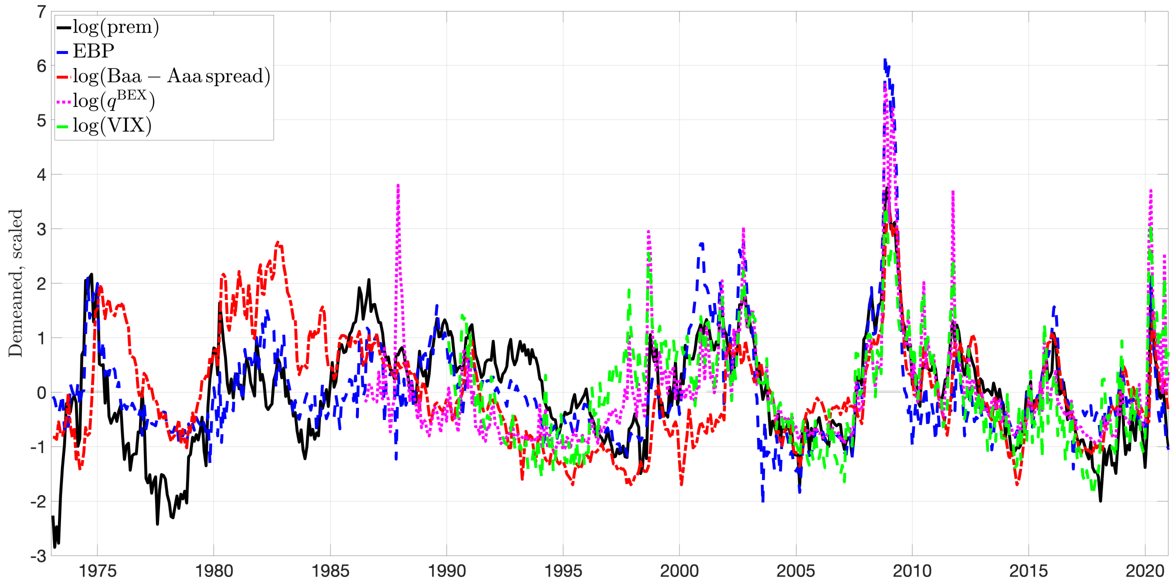

Figure B.1: Risk premium measure and proxies

The figure shows the monthly times of $\log(\text{prem}_t)$, from January 1975 to September 2021. It also displays alternative risk premium proxies, including the excess bond premium of Gilchrist and Zakrajšek (2012), the Baa-Aaa spread, the Bekaert, Engstrom, and Xu (2021) risk aversion measure (q^{BEX}), and the VIX index.

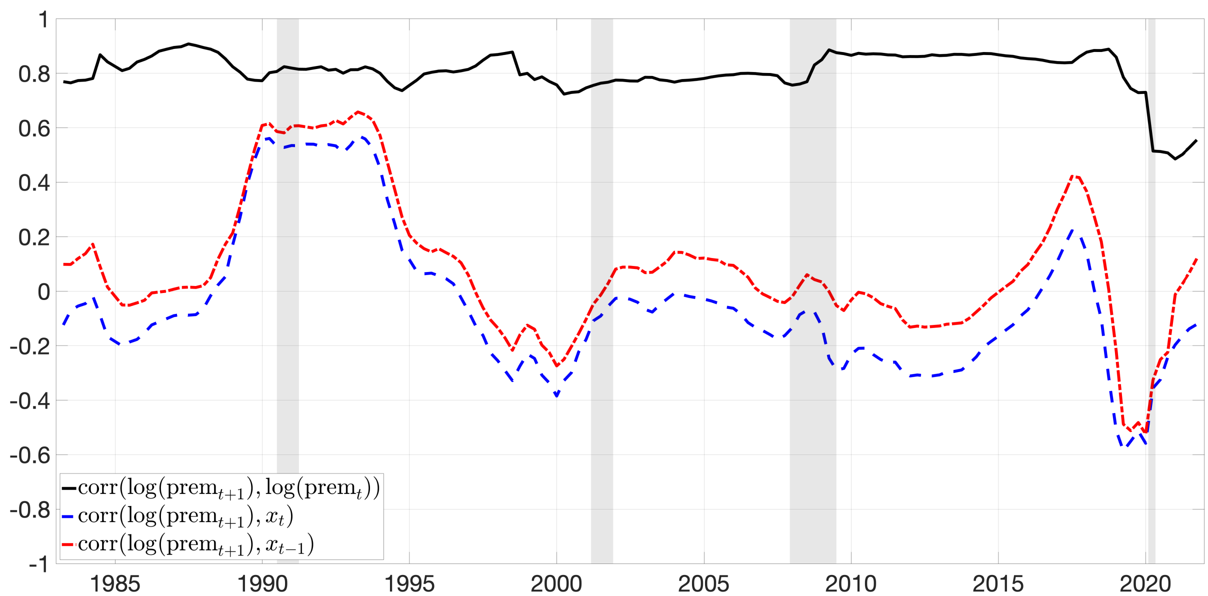

Figure B.2: Risk premium measure and proxies

The figure shows the trailing ten-year autocorrelation for the log risk premium (black solid line), correlation between log risk premium and once-lagged output gap (blue dashed line), and between log risk premium and twice-lagged output gap (red dashed line).

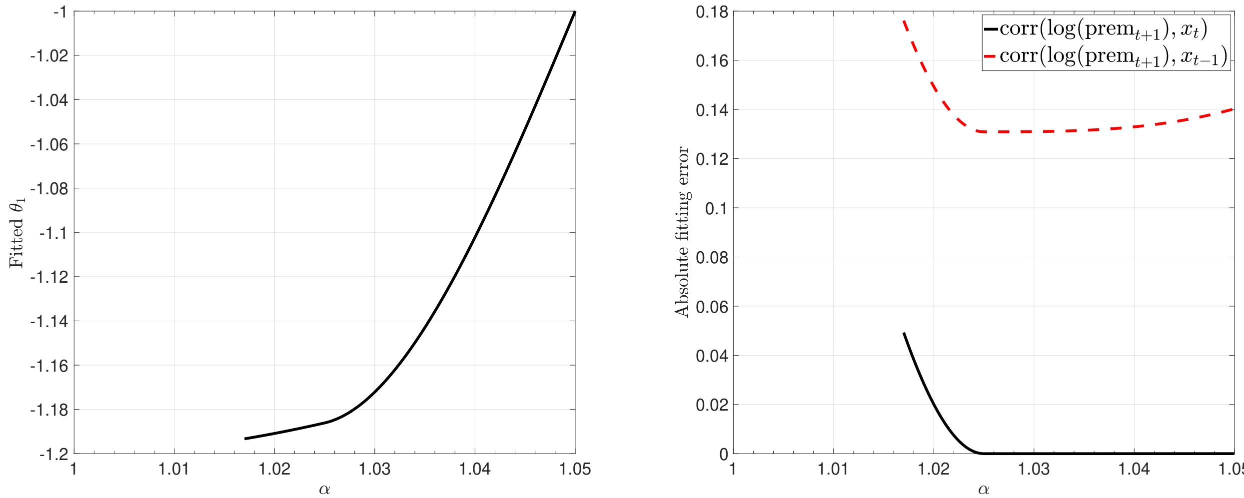

Figure B.3: Model-implied link between preferences and lagged output gap

For various values of α, the left panel shows the value for θ_1 at which the model-implied and observed valued for $\text{corr}(\log(\text{prem}_{t+1}), x_t)$ match as closely as possible. For each (θ_1, α), we choose σ_{MP} and θ_0 to match the model-implied annualized consumption volatility to its target value of 1.5% and the autocorrelation of the log market risk premium to its target value of 0.83 (Table 3). Only α values for which the model-implied standard deviations of real rates is between $\pm 1\%$ of its empirical target of 1.35% are shown. The right panel shows the corresponding absolute fitting errors for $\text{Corr}(\log(\text{prem}_{t+1}), x_t)$ and $\text{Corr}(\log(\text{prem}_{t+1}), x_{t-1})$.