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 from corporate bond price data and employ this approach to estimate empirical targets for the calibration of models that link such preferences to the output gap. Using a popular model that integrates macroeconomic dynamics with habit-based preferences, we show that our evidence on the market risk premium is most consistent with a model specification where a 1% monetary policy shock reduces output by 50–75 basis points, with the trough occurring at five to eight quarters, depending on the sample period. 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.

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A substantial body of literature examines 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, lags of the output gap are 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 the output gap affects risk preferences and, if it does, the extent to which it 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 variation in the surplus consumption ratio that allows us to quantify the impact of the output gap on preferences.

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 the surplus consumption ratio from the prices of corporate debt and calibrate macroeconomic dynamics to the observed relationship between this ratio 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 the surplus consumption ratio and the output gap aligns most closely with a model specification where a 100 basis point monetary policy shock reduces output by 0.55%, with the trough occurring at eight quarters. These estimates are similar to those of Christiano, Eichenbaum, and Evans (1999), who report a 0.7% reduction in output at eight quarters. The calibration suggests a longer-lived impact of monetary shocks when recession periods are included in the estimation of the sensitivity of preferences to lagged output. Excluding recessions in this estimation, the model-implied response of output to a 100 basis point monetary policy shock reaches -0.74% at five quarters. Recessions, particularly the Global Financial Crisis (GFC), increase the impact of lagged consumption growth—which serves as a benchmark combination of output lags—on preferences, resulting in a larger backward-looking coefficient in the Euler equation and, therefore, a more distant trough in the impulse response function.

Our approach ensures that the model accurately reflects the sensitivity of the non-AR(1) component of the log surplus consumption ratio to lagged consumption growth. While New Keynesian models sometimes impose the restriction that the forward- and backward-looking terms in the Euler equation sum to one (Dennis, 2009), our calibration allows this condition to emerge naturally, and it does so closely. Similar to Pflueger and Rinaldi (2022), our calibration generates realistic macroeconomic dynamics and equity returns, while somewhat overestimating interest rate volatility.

To extract a measure of time-varying market risk premia, and thus time-varying log surplus consumption ratios, 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. Our bond price data, covering publicly traded non-financial US companies from January 1973 to September 2021, are sourced from TRACE, the Lehman Brothers Fixed Income Database, and the Mergent FISD/NAIC Database. The analysis uses Moody's historical default data to estimate default probabilities and create a default news index, which aggregates deviations between realized default rates and estimated default probabilities across firms. This index is assumed to update in sync with macroeconomic news. We use the default news index to estimate a "default loss beta," capturing the sensitivity of defaults to economic shocks. The index varies over the business cycle in a manner consistent with increases in measured risk premia during recessions. By determining the portion of credit spreads attributable to default risk and exposure to the default news index, we can isolate and extract the market risk premia. Our estimations are similar if we exclude the years 1973–1985, when the high-yield segment of the corporate bond market was still in its infancy (Altman, 1987).

We compare our measure of time-varying risk premia to several established metrics: the excess bond premium (EBP) from Gilchrist and Zakrajšek (2012), the risk aversion variable from Bekaert, Engstrom, and

Xu (2021), the Baa-Aaa bond yield spread, and a stock-market volatility index. Our measure shows a high correlation with these alternatives. While our measure is explicitly designed to capture market risk premia, these other metrics aim to capture specific components of the market risk premium (e.g., excess premia, risk aversion, or market-wide volatility) or include additional factors such as default risk or clientele effects (e.g., Baa-Aaa bond yield spread). Therefore, they are inherently less suited to estimate the relationship between preferences and the output gap accurately. We provide evidence that cautions against calibrating preference dynamics using empirical targets based on measures that correlate with the market risk premium only imperfectly.

Our paper contributes to the literature that incorporates habit utility into a general equilibrium model of the economy, including work by Smets and Wouters (2003), Smets and Wouters (2007), Cochrane (2017), Campbell, Pflueger, and Viceira (2020), Fuhrer (2000), Bekaert, Engstrom, and Xu (2021) and Swanson (2021), and builds on the seminal work of Campbell and Cochrane (1999). Research that includes output in the habit equation (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 the surplus consumption ratio 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 Gallmeyer, Hollifield, and Zin (2005), Gallmeyer, Hollifield, and Zin (2007), Borio and Zhu (2012), Bekaert, Hoerova, and Lo Duca (2013), Bekaert, Engstrom, and Xu (2021), and Bauer, Bernanke, and Milstein (2023) 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 market risk premia and how the underlying data are sourced. Section 4 computes empirical targets that describe the comovement of risk premia and output gap lags, calibrates macroeconomic dynamics to these moments, and then produces the model-implied impulse response of output to monetary policy actions. Section 5 considers alternative risk premium measures. Section 6 concludes.

1. Model

This section describes the macroeconomy, habit preferences and the stochastic discount factor (SDF). 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}, where $\mathbb{E}_t(v_{t+1})$ is the conditional mean. The standard deviation is denoted by $\sigma_{v,t}$.[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,[2] such that $U(C_t) = [(C_t - H_t)^{1-\gamma} - 1]/(1-\gamma)$ 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.[3] 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 real SDF is given as

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

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

$$s_{t+1} = (1-\theta_0)\bar{s} + \theta_0 s_t + \theta_1 x_t + \theta_2 x_{t-1} + \lambda(s_t)\varepsilon_{c,t+1}, \tag{2}$$

[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] Habits are external in the sense that they are influenced by aggregate consumption rather than individual choices. Households do not internalize how their personal consumption affects overall habits.

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

for scalars θ_0, θ_1, and θ_2, and a steady-state value $\bar{s}$ of the log surplus consumption ratio. In equilibrium, the consumption surprise $\varepsilon_{c,t+1}$ is a scaled version of the normally distributed and homoskedastic fundamental shock. Its conditional standard deviation is denoted as σ_c. The sensitivity function takes the usual form,[4]

$$\lambda(s_t) = \begin{cases} \frac{1}{\bar{S}}\sqrt{1-2(s_t-\bar{s})}-1, & s_t \leq s_{max} \\ 0, & s_t > s_{max}, \end{cases} \tag{3}$$

with $\bar{S} = \exp(\bar{s}) = \sqrt{\gamma/(1-\theta_0)}\sigma_c$ and $s_{max} = \bar{s} + \frac{1}{2}(1-\bar{S}^2)$.

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,

$$x_t = c_t - (1-\phi)\sum_{j=0}^{\infty}\phi^j c_{t-1-j}, \tag{4}$$

for smoothing parameter ϕ. 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 (4) implies

$$\Delta c_t = x_t - \phi x_{t-1}, \tag{5}$$

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

Pflueger and Rinaldi (2022) emphasize that a non-zero value for θ_1 in Equation (2) is necessary to generate a hump-shaped output response to a monetary shock and they estimate its value by calibrating the model to empirical estimates of the hump's timing and magnitude (Christiano, Eichenbaum, and Evans, 1999). In contrast, we estimate θ_1 from the empirical properties of our risk aversion measure and use it to examine the shape of the output response.

[4] Campbell and Cochrane (1999) designed the sensitivity function (3) so that the log surplus consumption ratio s_t drops out of the Euler equation for real risk-free rates.

1b. Euler equation

The asset pricing first-order condition for the real risk-free rate r_t implies the Euler equation

$$r_t = -\log\left(\mathbb{E}_t(\exp(\Delta m_{t+1}))\right). \quad (6)$$

Substituting (1), (2) and (3) into (6), and simplifying, gives

$$r_t = \gamma\,\mathbb{E}_t(\Delta c_{t+1}) + \gamma\theta_1 x_t + \gamma\theta_2 x_{t-1}. \quad (7)$$

Further substituting (5) into (7), and rearranging terms, yields

$$x_t = f_x\,\mathbb{E}_t(x_{t+1}) + \rho_x x_{t-1} - \psi r_t, \quad (8)$$

where $\psi = \frac{1}{\gamma(\phi-\theta_1)}$, $f_x = \gamma\psi$ and $\rho_x = \theta_2\gamma\psi$. The sum of the forward- and backward-looking terms in the Euler equation (8) is denoted by

$$\alpha = f_x + \rho_x. \quad (9)$$

Some New Keynesian models assume that the forward- and backward-looking terms f_x and ρ_x sum to one ($\alpha = 1$).[5] This restriction is also imposed by Pflueger and Rinaldi (2022). However, similar to the approach of Campbell, Pflueger, and Viceira (2020), we do not assume a specific value for α. Instead, in our calibration, α is determined empirically based on estimates of the relationship between preferences and the lagged output gap, as detailed in Section 4. Our analysis indicates that α is close to, but slightly below, one. Moreover, the backward-looking coefficient ρ_x in the Euler equation (8) is positive and, across the full sample, slightly larger than its forward-looking counterpart.

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

1c. Monetary policy rule and Phillips curve

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

$$i_t = \rho_i i_{t-1} + (1-\rho_i) i_t^* + \nu_t, \tag{10}$$

for some inertia parameter $\rho_i \in (0,1)$. The monetary policy shock ν_t is the fundamental shock to macroeconomic dynamics, and is assumed to be normally distributed with mean zero and standard deviation σ_{MP}.

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: $r_t = i_t - \mathbb{E}_t(\pi_{t+1})$. Inflation π_t is determined by a log-linearized Phillips curve: $\pi_t = f_\pi \mathbb{E}_t(\pi_{t+1}) + \rho_\pi \pi_{t-1} + \kappa x_t$, for constants f_π, ρ_π and κ.[6]

1d. Equilibrium solutions

The macroeconomic state vector is given as $W_t = [x_t, \pi_t, i_t]'$. Its elements are normalized to have zero averages. The fundamental shock is ν_t. We are interested in an equilibrium solution of the form $W_t = BW_{t-1} + \Sigma \nu_t$, where B and Σ are $[3 \times 3]$ and $[3 \times 1]$ matrices, respectively. There may exist alternative equilibrium dynamics for W_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 this form. 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.

1e. 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

$$V_{Y,t} = \sum_{j=1}^{\infty} \mathbb{E}_t\left(\exp\left(\sum_{s=1}^{j} m_{t+s}\right) Y_{t+j}\right). \tag{11}$$

[6] Following the arguments in the appendix to Pflueger and Rinaldi (2022), the log-linearized Phillips curve 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 ($f_\pi + \rho_\pi = 1$).

It can be expressed as

$$V_{Y,t} \quad = \quad \mathbb{E}_t(\exp(m_{t+1}))\,\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})\,(1-\text{prem}_{Y+V_Y,t}), \tag{12}$$

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.[7] In Appendix A, we derive the approximate relationship $\text{prem}_{Y+V_Y,t} = \beta_{Y,t}\,\text{prem}_t$, where

$$\beta_{Y,t} \quad = \quad \frac{\text{Cov}_t\left(\varepsilon_{c,t+1}, \frac{Y_{t+1}+V_{Y,t+1}}{\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})}\right)}{\sigma_c^2} \tag{13}$$

is the claim's consumption news beta, and

$$\text{prem}_t \quad = \quad \gamma(1+\lambda(s_t))\sigma_c^2 \tag{14}$$

is the risk premium for the one-period consumption claim or, more generally, the risk premium on a one-period beta-one claim. Going forward, we refer to prem_t as the "market risk premium."

According to (3), temporal variation in prem_t reflects variation in s_t. Substituting (3) into (14) gives

$$\log(\text{prem}_t) \quad = \quad \frac{1}{2}\log(1-2(s_t-\bar{s})), \tag{15}$$

which holds up to a constant.

In the remainder of this section and the next, we detail our method for extracting $\log(\text{prem}_t)$ and, consequently, variation in s_t, from corporate bond price data. With this in hand, we are able to estimate parameters in the preference specification given by Equation (2), and ultimately to elucidate the relationship between interest rates and output.

1f. Corporate bonds

While the pricing concept (11)–(14) 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

[7] 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.

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

$$B_{it} \quad = \quad \mathbb{E}_t(\exp(m_{t+1}))(1-\mathrm{cs}_{it}), \tag{16}$$

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

$$\mathrm{cs}_{it} \quad = \quad \mathbb{E}_t(L_{i,t+1}) + \mathbb{E}_t(1-L_{i,t+1})\,\mathrm{prem}_{1-L,it}. \tag{17}$$

The credit spread in excess of expected losses is measured by $\mathrm{cs}_{it} - \mathbb{E}_t(L_{i,t+1})$. We distinguish between observed credit spreads, denoted by $\widehat{\mathrm{cs}}_{it}$, and the model-based spreads cs_{it} in (17), to allow for observed excess spreads $\widehat{\mathrm{cs}}_{it} - \mathbb{E}_t(L_{i,t+1})$ to include a proportional illiquidity mark-up $\exp(\ell_{it})$, so that

$$\widehat{\mathrm{cs}}_{it} - \mathbb{E}_t(L_{i,t+1}) \quad = \quad \mathbb{E}_t(1-L_{i,t+1})\,\mathrm{prem}_{1-L,it}\,\exp(\ell_{it}). \tag{18}$$

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

Equation (18) gives observed excess spreads, per unit of expected losses, as

$$\frac{\widehat{\mathrm{cs}}_{it} - \mathbb{E}_t(L_{i,t+1})}{\mathbb{E}_t(L_{i,t+1})} \quad = \quad -\beta_{L,it}\,\mathrm{prem}_t\,\exp(\ell_{it}), \tag{19}$$

where $\beta_{L,it} = -\beta_{1-L,it}\,\mathbb{E}_t(1-L_{i,t+1})/\,\mathbb{E}_t(L_{i,t+1})$ 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 the market risk premium prem_t in Equation (19), up to a multiplicative constant. This requires estimates of default loss betas,

$$\beta_{L,it} = \frac{1}{\sigma_c^2}\text{Cov}_t\left(\varepsilon_{c,t+1}, \frac{L_{i,t+1}}{\mathbb{E}_t(L_{i,t+1})}\right). \tag{20}$$

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 (20), we set $\beta_{L,it} = \beta_{L,j_{it}t}$ where

$$\mathbb{E}_t\left(\frac{L_{j,t+1}}{\mathbb{E}_t(L_{j,t+1})} - 1 \middle| \varepsilon_{c,t+1}\right) = \beta_{L,j_{it}t}\varepsilon_{c,t+1}. \tag{21}$$

Equation (21) assumes that default loss expectations update proportionally with consumption news (or, equivalently, fundamental shocks).

To estimate $\beta_{L,jt}$ we need to relate innovations in default risk to fundamental shocks. Hilscher and Wilson (2017) show that credit ratings capture firms' exposure to systematic risk reasonably well. Thus, we form cohorts using credit ratings. For each date t and rating category j_t, we calculate $\zeta_{j,t+1}$ 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.[8] 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, $L_{j,t+1}/\mathbb{E}_t(L_{j,t+1}) = \zeta_{j,t+1}/P_{jt}$ holds and Equation (21) links unexpected defaults to consumption news via

$$\mathbb{E}_t\left(\frac{\zeta_{j,t+1}}{P_{jt}} - 1 \middle| \varepsilon_{c,t+1}\right) = \beta_{L,jt}\varepsilon_{c,t+1}. \tag{22}$$

We will document countercyclical increases in unexpected defaults across cohorts, indicating *(i)* common temporal variation in default news across cohorts, and *(ii)* a negative relationship between this common

[8] Importantly, in estimating cohort-level default rates we link default rates to market conditions, meaning our default predictions P_{jt} update through the business cycle. The estimation of P_{jt} is described in more detail later in the section.

variation and consumption news. We therefore construct a "default news index" as the first principal component of cohort-specific default shocks,

$$z_{t+1} = \sum_{j=1}^{J} \omega_j \left(\zeta_{j,t+1} - P_{jt}\right), \tag{23}$$

and assume that this index moves in lockstep with consumption news,

$$\mathbb{E}_t\left(z_{t+1} \middle| \varepsilon_{c,t+1}\right) = -b\varepsilon_{c,t+1}, \tag{24}$$

for a positive scalar b. The weights $\omega_j \in [0,1]$ sum to one and are chosen such that z_{t+1} inherits the maximum possible variance from the cohort-specific default news. Equation (24) differs from (22) in that, at the index level, comovement between default news and consumption news remains constant.

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

$$\mathbb{E}_t\left(\zeta_{j,t+1} - P_{jt} \middle| \varepsilon_{c,t+1}, z_{t+1}\right) = K_j z_{t+1}, \tag{25}$$

which implies

$$\beta_{L,jt} = -b\frac{K_j}{P_{jt}}. \tag{26}$$

2a. Cohort-specific default news

We now describe the process for measuring cohort-specific default news, $\zeta_{j,t+1} - P_{jt}$. We express $\zeta_{j,t+1}$ and P_{jt} in annualized form and, for robustness purposes, calculate them using their annualized five-year counterparts. The calculation relies on realized default data reported in Moody's Default and Recovery Rate Database. To construct the time series $\zeta_{j,t+1}$, we filter the entire Moody's database for US non-financial corporates. For each issuer-level letter[9] rating j and beginning of month t, we compute the realized cumulative default rate over the next five years, as shown in Figure B.1.

To predict cohort-level default rates P_{jt}, for each month from January 1973 onwards, we estimate beta

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

regression models[10] with a logit link function of past annualized five-year default rates:

$$\log\left(\frac{\zeta_{j,t+1}}{1+\zeta_{j,t+1}}\right) = a_j + Z_t b_j' + \varepsilon_{j,t+1}. \tag{27}$$

The vector of conditioning variables Z_t includes recent equity market conditions and forecasts of economic activity. The choice of conditioning variables is constrained by the need for a long consistent time series that pre-dates the beginning of our sample period in 1973 by no less than five years. Given that the highest rated bonds rarely default, the time series would ideally include several recessions that lead to a sharp increase in the probability of default. The regressions (27) are estimated for each rating cohort separately, using all available 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.

The regression results are summarized in Table B.1. Column (1) of each rating category panel shows the most basic specification, where the probability of default is simply an updated average of the last five years of default history for the rating category. Adding the trailing 12-month return on the S&P 500 index, such as in model (2), does not improve the prediction model by much. In contrast, adding in a GDP forecast, as in column (3), reduces the mean square error markedly for all five rating categories. The best fit is shown in column (4), and is accomplished by including the term spread as well as the previous two measures of economic activity. Going forward, we employ the default probability estimates based on specification (4).

Each end-of-month t (or, equivalently, beginning-of-month $t+1$), we use the estimated beta regression and the variables in Z observed at end-of-month t to compute P_{jt}^5 as the predicted five-year cumulative default rate for cohort j. Annualized five-year rates are given as $P_{jt}^{5a} = 1-(1-P_{jt}^5)^{1/5}$. Figure B.2 shows the monthly time series of estimated P_{jt}^{5a} by letter rating j. As expected, the predicted probabilities are higher for the lower ratings, as well as more volatile. Earlier in the sample period, there are fewer speculative-grade bonds at risk of default, adding to the volatility of the BB and B categories. Higher volatility in these categories also arises from a larger fraction of firms with unintentionally high leverage. In contrast, many of the lower rated issuers in 1986 and onward are firms that chose to maintain highly leveraged capital structures (Altman, 1987).

Using the actual and predicted default rates $\zeta_{j,t+1}$ and P_{jt}, Figure 1 displays the default news $\zeta_{j,t+1} - P_{jt}$.

[10]Regressions use the Stata command “betareg,” with the default logit link function and robust standard error estimates.

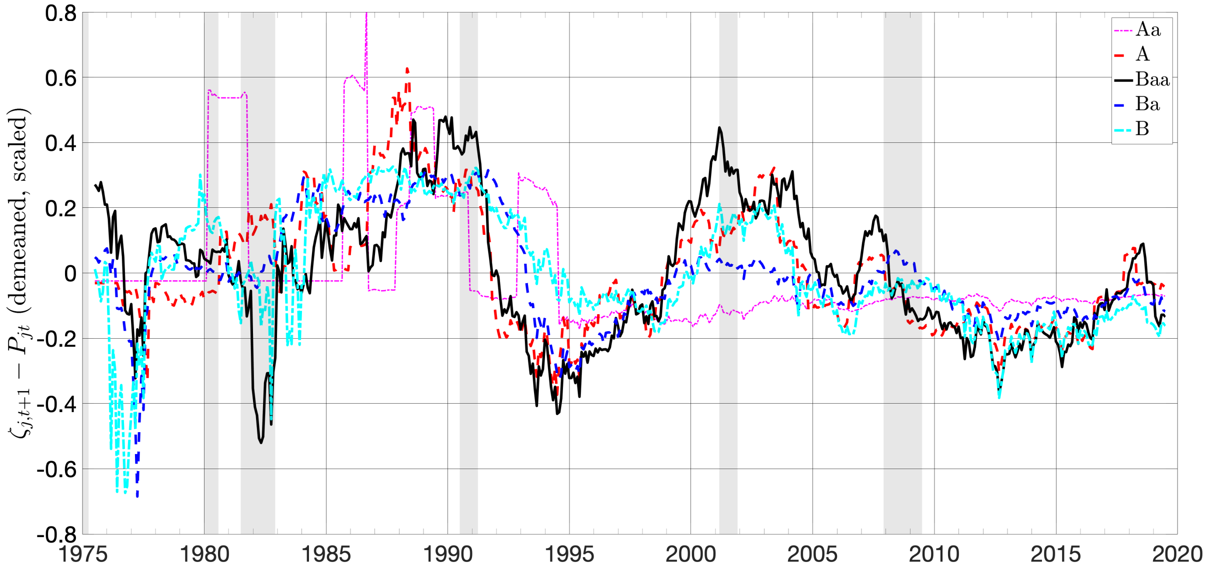

Figure 1: Cohort-specific default news

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 are shown in Figure B.1. Annualized default probabilities P_{jt} are estimated as in Figures B.2. 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 $t + 2.5$. All time series are demeaned and scaled by their max-min range. The shaded areas indicate NBER recessions.

The graph reveals considerable common countercyclicality in default news across cohorts.

2b. Calibration of default loss betas

Table 1: Default loss beta calibration

Standard deviation of default news					**Eigenvalues for first principal component**				
Aa	A	Baa	Ba	B	Aa	A	Baa	Ba	B
0.07	0.12	0.28	1.39	2.81	0.28	0.47	0.47	0.50	0.48
Index weights ω_j					**Default loss beta parameter K_j**				
ω_{Aa}	ω_A	ω_{Baa}	ω_{Ba}	ω_B	K_{Aa}	K_A	K_{Baa}	K_{Ba}	K_B
0.39	0.39	0.16	0.04	0.02	0.19	0.57	1.35	7.08	13.75

The table describes the inputs to and outputs of the principal component analysis of cohort-level default news, and reports the fitted parameters for Equations (23) and (25).

We set the weights ω_j used to construct the default news index in Equation (23) to the (scaled) eigenvalues of the correlation-based first principal component of cohort-specific default news, $\zeta_{j,t+1} - P_{jt}$. For each cohort j, we obtain K_j as the regression coefficient of $\zeta_{j,t+1} - P_{jt}$ on z_t. The estimates of ω_j and K_j are shown in Table 1. The table reports that the loadings ω_j on the default news index are larger for higher-credit-quality cohorts.

The default news index z_{t+1} constructed from the parameters in Table 1 is shown in Figure 2. The graph shows considerable cyclicality in the index, supporting our view that it represents the systematic component of cohort-level default risk.

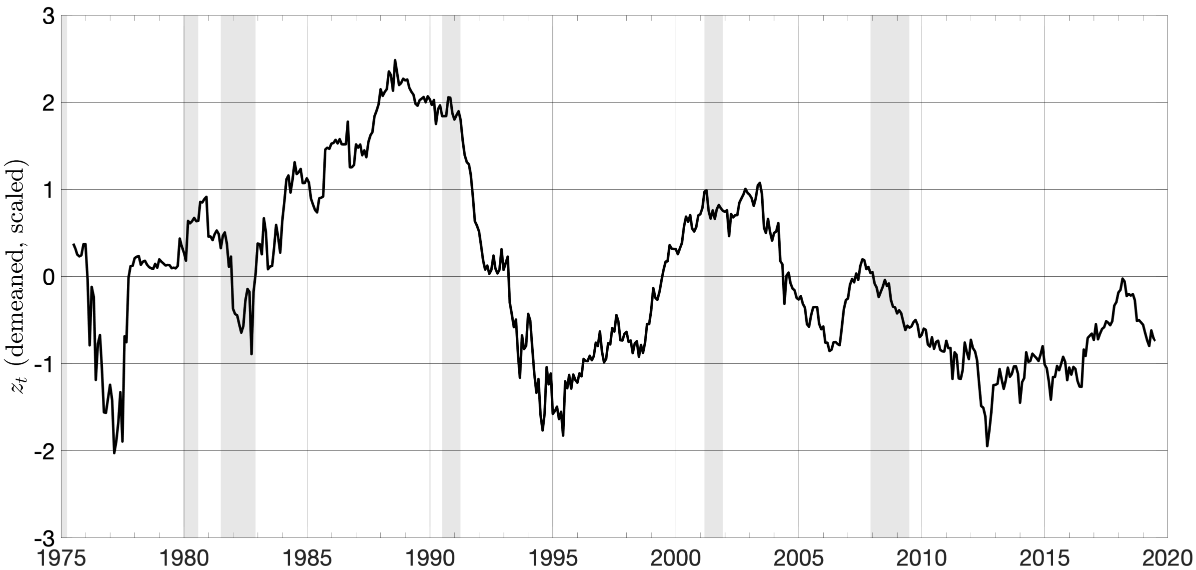

Figure 2: Default news index

The figure shows the fitted time series of the default news index z_t in Equation (23), based on the data in Figure 1 and the parameter estimates in Table 1. The shaded areas indicate NBER recessions.

Using the parameters K_j reported in the bottom right panel of Table 1, we compute default loss beta estimates according to (26). These beta estimates inherit their temporal variation from $1/P_{jt}$, and their cross-sectional variation from K_j/P_{jt}.

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 (19) 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, (19) is equivalent to

$$\log\left(\frac{\widehat{\text{cs}}_{jt} - \mathbb{E}_t(L_{j,t+1})}{\mathbb{E}_t(L_{j,t+1})}\right) \quad = \quad \log(-\beta_{L,jt}) + \log(\text{prem}_t) + \ell_j. \tag{28}$$

Having obtained estimates of default loss betas, we can now use them to estimate the risk premium x_t. Specifically, substituting (26) into (28) gives

$$\log\left(\frac{\widehat{\text{cs}}_{jt}-\mathbb{E}_t(L_{j,t+1})}{K_{jt}}\right) \quad = \quad \log(\text{prem}_t)+\ell_j. \tag{29}$$

which allows us to estimate $\log(\text{prem}_t)$ as time fixed effects in a regression of the left-hand side in (29) 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 US-domiciled firms.[11] 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.[12] 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.[13] 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.[14] 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.

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

[11] 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.

[12] 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.

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

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

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 data for less than 12 months are excluded. This leaves us with 162,540 firm-month observations, covering 1,469 public non-financial US firms over the period January 1973 to September 2021.

The range of credit quality in our data may be judged from Table B.2, 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. 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.[15] Figure 3 plots average credit spreads by letter rating for our sample. As expected, spreads are highest for firms with the lowest credit rating. Credit spreads rise around recessions, before reverting back to lower levels.

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 (2022) as of 2.5 years prior to default, for the period 1983–2021.

[15] While the number of investment-grade utilities in our sample exceeds that of high-yield utilities (Table B.2), there are more firm-month observations for riskier utilities. This explains the fairly high value of median credit spreads for the utilities sector in Table B.3.

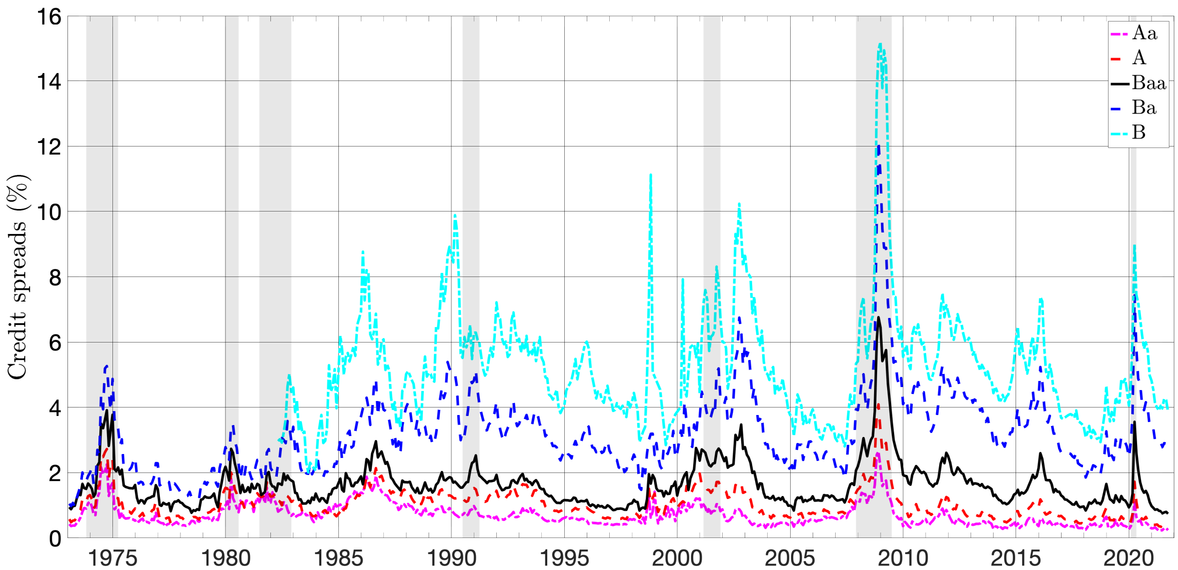

Figure 3: Credit spreads by letter rating

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. The shaded areas indicate NBER recessions.

3b. Estimation results

We estimate $\log(\text{prem}_t)$ as time fixed effects in a regression of the left-hand side in Equation (29) 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.

Table 2: Risk premium identification

	constant	Aa	A	Ba	B	Mo FEs	R-sqr	RMSE	Obs
Est	-4.669**	1.065**	0.475**	-1.243**	-1.937**	✓	0.944	0.316	2786
SE	(0.219)	(0.015)	(0.012)	(0.015)	(0.024)				

This table reports the estimation results for the model in Equation (29), which identifies $\log(\text{prem}_t)$ as the month fixed effects in a panel-data 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 from January 1973 to September 2021. We use ** to denote significance at the 1% level.

We plot the time series of $\log(\text{prem}_t)$ in Figure 4. 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 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 lift off the zero lower bound.

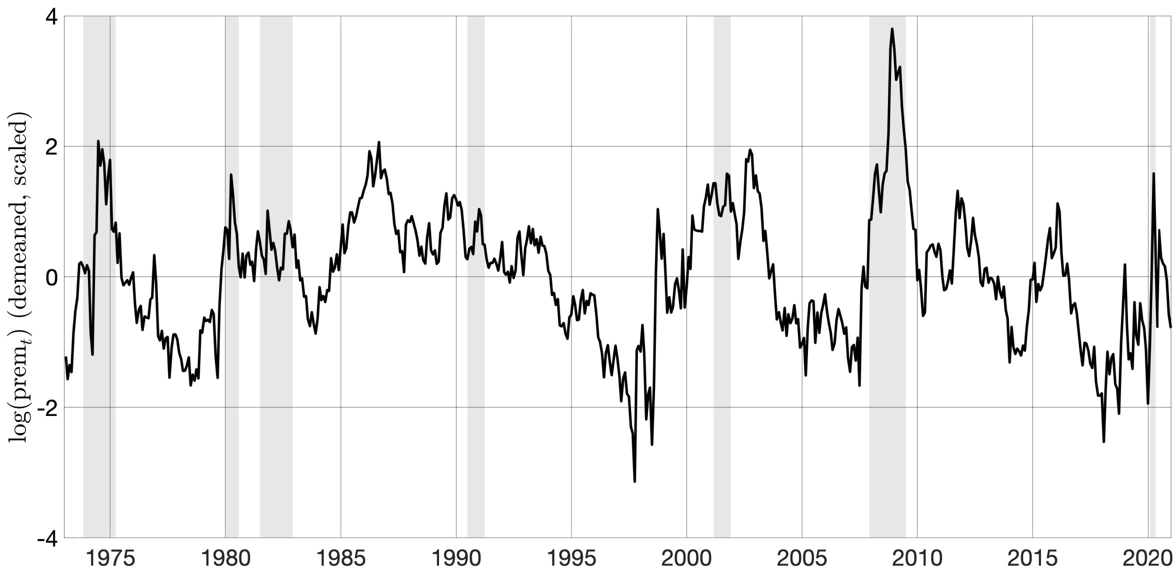

Figure 4: Market risk premium

The figure shows the monthly time series of $\log(\text{prem}_t)$, from January 1973 to September 2021. The displayed time series is demeaned and scaled by its standard deviation. The shaded areas indicate NBER recessions.

4. Preference Dynamics and Macroeconomic Fundamentals

Our main focus is on the calibration of the relationship (2) which, for a non-zero θ_1, we rewrite as

$$(s_{t+1} - \bar{s}) - \theta_0(s_t - \bar{s}) \quad = \quad \theta_1 \left(x_t + \frac{\theta_2}{\theta_1} x_{t-1} \right) + \lambda(s_t)\varepsilon_{c,t+1}. \tag{30}$$

In the special case where $\theta_2 = -\phi\theta_1$, the term "$x_t + \frac{\theta_2}{\theta_1} x_{t-1}$" simplifies to consumption growth, $\Delta c_t = x_t - \phi x_{t-1}$, as per Equation (5). For ease of interpreting the relationship in Equation (30), and to facilitate a more robust estimation of θ_1 and θ_2, we restrict our analysis to this special case, and the resulting preference dynamics

$$(s_{t+1} - \bar{s}) - \theta_0(s_t - \bar{s}) \quad = \quad \theta_1 \Delta c_t + \lambda(s_t)\varepsilon_{c,t+1}. \tag{31}$$

Equation (31) identifies θ_1 as the sensitivity of the non-AR(1) component of the log surplus consumption ratio to lagged consumption growth. While we cannot observe s_t directly, substituting (3) into (14) gives the approximate relationship

$$\log(\text{prem}_t) \quad = \quad -(s_t - \bar{s}), \tag{32}$$

which holds when s_t is close to its steady state $\bar{s}$,[16] and up to a constant. Thus, near the steady state, Equations (31) and (32) allow us to estimate θ_1 as the negative of the regression coefficient of $\log(\text{prem}_{t+1}) - \theta_0 \log(\text{prem}_t)$ on Δc_t. When implementing the regression, we measure $\log(\text{prem}_t)$ as in Figure 4 and compute Δc_t as in Equation (5), with the log output gap sourced from the St. Louis Fed's economic data depository (FRED).[17]

The resulting estimates for θ_1 are summarized in Panel A of Table 3. Over the full sample period from 1973.I to 2021.III, the regression coefficient of $-(\log(\text{prem}_{t+1}) - \theta_0 \log(\text{prem}_t))$ on Δc_t is estimated at -1.47. This estimate remains similar, at -1.52, if we exclude the years prior to 1986, when the high-yield segment of the corporate bond market was still underdeveloped (Altman, 1987). The θ_1 regression coefficient estimates are generally not statistically different from zero.[18] In that sense, empirical support for a non-zero value of θ_1 in the specification of the preference dynamics in Equation (30) is limited. That said, a formal specification test of the preference dynamics proposed by Campbell, Pflueger, and Viceira (2020) is outside the scope of our paper. Instead, we input an empirical point estimate of θ_1 into their proposed preference dynamics and quantify what it implies about the response of output to monetary policy shocks.

We compute $\log(\text{prem}_{t+1}) - \theta_0 \log(\text{prem}_t)$ using the persistence parameter $\theta_0 = 0.87^{1/4}$, and $\Delta c_t = x_t - \phi x_{t-1}$ using the smoothing parameter $\phi = 0.93$. The persistence of the log surplus consumption ratio comes directly from Campbell and Cochrane (1999), and the smoothing parameter for detrending potential output is estimated by Campbell, Pflueger, and Viceira (2020). Table B.5 lists the additional model input parameters, the articles that these parameter values are drawn from, and the moments in the data that the literature has targeted with these parameters. As in Pflueger and Rinaldi (2022), we take the utility curvature parameter of $\gamma = 2$ and the parameters for consumption growth and the real risk-free rate from directly from Campbell and Cochrane (1999). The monetary policy parameters are set to the standard values reported by Taylor (1993) and Clarida, Gali, and Gertler (2000). The Phillips curve draws its parameterization from Fuhrer (1997) and Hazell, Herreno, Nakamura, and Steinsson (2022).

For the full sample, the estimated preference parameter θ_1 together with the model input parameters listed in Table B.5 imply $\theta_2 = -\phi\theta_1 = 1.37$, an annualized discount factor of 0.9, and an Euler equation

[16] A higher-order Taylor approximation of Equation (15) is $\log(\text{prem}_t) = -(s_t - \bar{s}) - \frac{2}{2}(s_t - \bar{s})^2 - \frac{2^2}{3}(s_t - \bar{s})^3 - \frac{2^3}{4}(s_t - \bar{s})^4 \ldots$.

[17] Specifically, $x_t = \log(\text{GDPC1}/\text{GDPPOT})$, where GDPC1 is the real GDP in billions of chained 2012 dollars and GDPPOT is the real potential GDP, also in billions of chained 2012 dollars.

[18] They remain insignificant even when the restriction $\theta_2 = -\phi\theta_1$ is lifted, and $\log(\text{prem}_{t+1}) - \theta_0 \log(\text{prem}_t)$ is regressed on $x_t + \frac{\theta_2}{\theta_1} x_{t-1}$.

Table 3: Estimated parameters and moments

		Full 1973.I–21.III	Post-85 1986.I–21.III	Post-85, excl. recessions
Panel A: Estimated parameters				
Surplus consumption–lagged output gap	θ_1	−1.468	−1.516	−1.026
SD annual MP shock (%)	σ_{MP}	1.780	1.870	1.150
Panel B: Implied parameters				
Surplus cons–twice-lagged output gap	θ_2	1.37	1.41	0.95
Discount rate (annualized)	β	0.90	0.90	0.90
Steady-state surplus cons ratio	$\overline{S}$	0.03	0.03	0.03
Maximum surplus cons ratio	$S^{\max}$	0.05	0.05	0.05
Euler eq forward coefficient	f_x	0.42	0.41	0.51
Euler eq backward coefficient	ρ_x	0.57	0.58	0.49
Forward + backward coeff in Euler eq	α	0.986	0.985	0.999
Euler equation real rate slope	ψ	0.21	0.20	0.26
Panel C: Implied macroeconomic dynamics				
SD annual consumption growth	Model	1.50	1.50	1.50
	Data	1.50	1.50	1.50
Trough effect output (%)		−0.55	−0.53	−0.74
Lag trough (quarters)		8	8	5
Panel D: Model and empirical moments: Equity				
Equity premium (%)	Model	8.47	8.66	7.14
	Data	7.30	8.66	12.06
Volatility (%)	Model	17.36	17.78	14.54
	Data	17.74	17.26	14.75
Sharpe ratio	Model	0.49	0.49	0.49
	Data	0.41	0.50	0.82
Panel E: Model and empirical moments: Bonds				
SD annual change Fed Funds rate (%)	Model	3.32	3.49	2.11
	Data	2.15	1.39	1.25

Panel A presents the estimates for the model parameters θ_1 and σ_{MP}. The parameter θ_1 is estimated as the coefficient in a regression of $-(\log(\text{prem}_{t+1}) - \theta_0 \log(\text{prem}_t))$ on Δc_t. The estimates reported in the first, second, and third columns are based on quarterly data spanning from 1970.I to 2021.III, from 1986.I to 2021.III, and from non-recession periods between 1986.I and 2021.III, respectively. For each period, the parameter σ_{MP} is chosen to calibrate the model to match model-implied consumption volatility at 1.5%. Panel B displays the parameters implied by the calibration, while Panel C records model-implied macroeconomic moments. The asset pricing estimates shown in Panels D and E are calculated using the numerical approximation and public code of Pflueger and Rinaldi (2022).

with roughly equal-sized forward- and backward-looking coefficients ($f_x = 0.42, \rho_x = 0.57$). The sum of these two coefficients is 0.99, so slightly less than one. The coefficient on the real interest rate in the Euler equation is 0.21, which is closely in line with the estimate in Yogo (2004) of 0.2.

Using our θ_1 estimate and the input and implied parameters, we simulate the model for various values for the standard deviation of monetary policy shocks, σ_{MP}. The simulation runs for a length of $T = 10,000$ periods, discarding the first 100 periods to ensure that the system reaches the stochastic steady-state. Table B.6

shows the model-implied macroeconomic dynamics as a function of σ_{MP}. Like Pflueger and Rinaldi (2022), we target an unconditional volatility of annual changes in log consumption of 1.5% reported in Campbell and Cochrane (1999). For the full sample, this target moment is met at $\sigma_{\text{MP}} = 1.78\%$.

Panel C of Table 3 indicates that the model suggests the trough in output response occurs eight quarters following the initial monetary policy shock, with an estimated decrease of approximately 55 basis points for every 100 basis point increase in the Fed Funds rate. These estimates closely align with those of Christiano, Eichenbaum, and Evans (1999), who derived similar figures using a structural VAR model, reporting an output reduction of 70 basis points at eight quarters. Using the estimates from the post-1985 period, we find similar results: the trough remains at eight quarters and the effect of a monetary policy shock on output is nearly the same.

Figure 5 illustrates the transmission of a 100 basis point monetary policy shock. Shown in the top panel, full-sample estimates indicate that the shock leads to an increase in the risk-free rate that mean-reverts and converges back to zero at about eight to nine quarters. Output shows an initial decline, reaching a trough response of approximately -0.55 percentage points at eight quarters, before gradually returning to its steady-state level. The response of the output gap is slightly less pronounced, reaching a trough of about -0.42 percentage points around five quarters after the initial shock. We obtain similar impulse response functions when the sample is restricted to 1986 and later (Panel B of the figure).

4a. Asset pricing implications

To evaluate how effectively the macroeconomic model, when integrated with preference dynamics calibrated to our credit-market-based risk premium measure, prices other asset classes, we utilize the public source code from Pflueger and Rinaldi (2022) to compute model-implied equity and Treasury bond prices. These prices depend on both the macroeconomic state vector W_t and the log surplus consumption ratio s_t in a highly non-linear form. The price of equity, P_t^{δ}, is set to the price of the claim to aggregate consumption, P_t^c, times the leverage factor δ, as described in Table B.5. The price-consumption ratio for the claim to aggregate consumption is given as the infinite sum of the price-consumption ratios for n-period zero consumption claims,

$$\frac{P_t^c}{C_t} = \sum_{n=1}^{\infty} \frac{P_{n,t}^c}{C_t}, \tag{33}$$

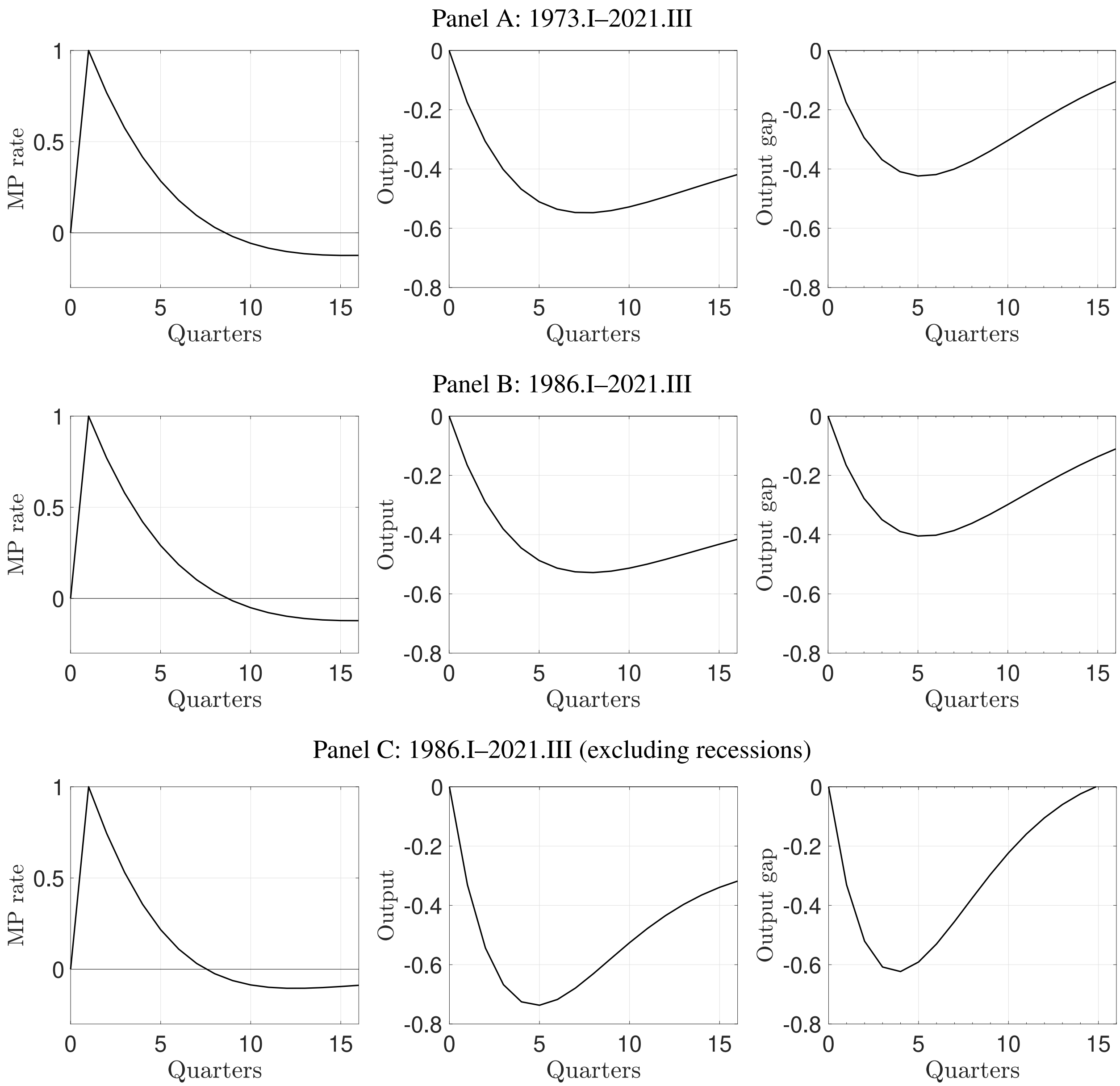

Figure 5: Model-implied impulse responses to monetary policy shock

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 output in percent, and the right panel shows the response of the output gap in percent.

with the n-period claim is priced at

$$\frac{P^c_{n,t}}{C_t} \quad = \quad \mathbb{E}_t\left(M_{t+1}\frac{C_{t+1}}{C_t}\frac{P^c_{n-1,t+1}}{C_{t+1}}\right). \tag{34}$$

The provided code uses numerical methods to find the solution to the recursion in Equation (33). Further details are available in the online appendix to Pflueger and Rinaldi (2022).

Panels D and E of Table 3 outline the model's implications for pricing equity and Treasury bonds. Notably, the model effectively captures the equity premium, equity volatility, and Sharpe ratio. Restricting the sample period to 1986 and later, the model is even closer to the equity data. However, these results suggest a standard deviation of annual changes in the Fed Funds rate that is quite high (3.32% in the full sample, exceeding the empirical target of 2.15%). This result arises, as it does in Pflueger and Rinaldi (2022), because the model's macroeconomic dynamics are driven by a single shock. Therefore, the calibration can either match consumption volatility or interest-rate volatility, but not both. Given that consumption volatility plays a crucial role in Equation (30) for preference dynamics, we align with Pflueger and Rinaldi (2022) in targeting consumption volatility rather than interest-rate volatility.

4b. Excluding recessions when estimating θ_1

Since preferences may deviate more heavily from the steady state in bad times than in good times, we re-calibrate the model by excluding NBER recessions from the post-1985 sample period. The results are reported in the third column of Table 3. After excluding recessions from the regression of $\log(\text{prem}_{t+1}) - \theta_0 \log(\text{prem}_t)$ on Δc_t, the θ_1 estimate is revised to -1.03. This reflects a somewhat smaller (in absolute value) measured impact of lagged consumption growth on preferences.

For this calibration, the consumption volatility target moment is met at $\sigma_{\text{MP}} = 1.15\%$. The Euler equation has nearly equal-sized forward- and backward-looking coefficients ($f_x = 0.51, \rho_x = 0.49$), with their sum essentially equal to one. The model indicates that the trough in output response occurs five quarters after the initial monetary policy shock, with an estimated decrease of approximately 74 basis points for a 100 basis point increase in the Fed Funds rate. These estimates closely align with those targeted by Pflueger and Rinaldi (2022), who calibrate their model to an output reduction of 70 basis points at four to six quarters. While Pflueger and Rinaldi (2022) calibrate their model to the "70 basis points at four to six quarters" relationship between the Fed Funds rate and output, we extract a measure of the surplus consumption ratio from corporate debt prices and calibrate macroeconomic dynamics to the observed relationship between this ratio and the output gap. Importantly, our approach yields the impulse response function of output to monetary policy shocks as a model output, rather than taking it as a model input.

5. Alternative Proxies of Market Risk Premia

As proxies for the market risk premium, one might also consider several well-known measures of risk in the corporate bond literature: the Baa-Aaa spread, the excess bond premium (EBP) measure from Gilchrist and Zakrajšek (2012), and the risk aversion (RA) variable in Bekaert, Engstrom, and Xu (2021). The Baa-Aaa spread is sourced from FRED. It is the difference between the average yield on Baa-rated bonds and that of Aaa-rated bonds, and it is affected by the differences in both the expected losses and default loss betas of Baa and Aaa bonds. By comparing the Baa yield to the Aaa yield, the Baa spread is less affected by liquidity than if it were measured against a comparable maturity Treasury bond. The EBP measure is based on all corporate bond spreads rather than just those of the Baa and Aaa bonds. It removes *all* variation from credit spreads that is related to variation in expected losses, but it does not necessarily represent a market risk premium as controlling for expected loss variation may also (partially) control for risk premium variation. Both the Baa spread and the EBP measure are available for the entire sample period. The RA measure from Bekaert, Engstrom, and Xu (2021), which relies on the VIX to extract risk premia from corporate bond spreads, is only available for the time period when the VIX exists (from 1986 onwards). The VIX itself may proxy for time-varying risk aversion.[19]

Because our macroeconomic results hinge on the robustness of the log(prem) estimate of the market risk premia, we provide additional details on this measure here. Figure 6 plots the risk premium proxies from the literature against the benchmark version of our market risk premium. The figure shows that the five measures often move together. All of them reach a peak in the 2008–2009 period, and tend to be lower between recessions. Table B.4 further supports the generally high correlations between the various measures.

While our log(prem) measure is explicitly designed to capture market risk premia, the other metrics in Figure 6 aim to capture specific components of the market risk premium (e.g., excess premia, risk aversion, or market-wide volatility) or include additional factors such as default risk or clientele effects (e.g., Baa-Aaa bond yield spread). Therefore, these alternative metrics are inherently less suited for accurately estimating the relationship between preferences and output. Table B.7 provides evidence that cautions against calibrating preference dynamics using empirical targets based on measures that only imperfectly correlate with the market risk premium. Specifically, it reports the θ_1 estimates resulting from a regression of (minus)

[19]The SVIX variable from Martin (2017), which is available from 1996 to 2012, offers another alternative. We note that it is very highly correlated with the RA measure of Bekaert, Engstrom, and Xu (2021) during the period.

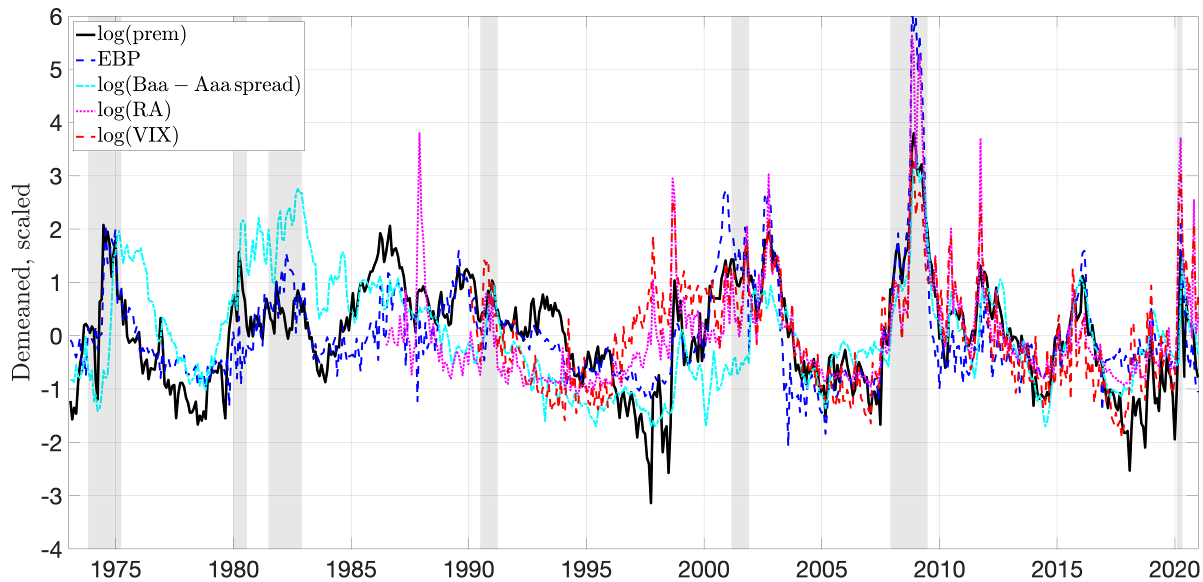

Figure 6: Risk premium measure and proxies

The figure shows the monthly time series of $\log(\text{prem}_t)$, from January 1973 to September 2021. It also displays alternative risk premium proxies, including the excess bond premium (EBP) of Gilchrist and Zakrajšek (2012), the log Baa-Aaa spread, the log Bekaert, Engstrom, and Xu (2021) risk aversion measure (RA), and the log VIX index. The displayed time series are demeaned and scaled by their respective standard deviations. The shaded areas indicate NBER recessions.

$\text{EBP}_{t+1} - \theta_0 \text{EBP}_t$, instead of $\log(\text{prem}_{t+1}) - \theta_0 \log(\text{prem}_t)$, on Δc_t. While the EBP-based θ_1 estimate of $1 - 1.18$ is close to its log(prem)-based counterpart when recessions are excluded from the sample, it falls below -2 when recessions are considered. As shown in Panels A and B of Table B.7, at $\theta_1 < -2$, the model can match consumption volatility only at the expense of an overly high interest rate volatility. For estimations derived from data where the log surplus consumption ratio tends to be near the steady state, EBP-based results are consistent with our benchmark findings, estimating the trough of the output response to monetary policy shocks at -0.74% at five quarters (Panel C). However, when recessions are included in the sample, EBP-based results imply a high upward bias in model-implied interest-rate volatilities.

6. Concluding Remarks

We present empirical evidence on the relationship between the surplus consumption ratio and lags of the 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), allowing us to evaluate elements of the preference specification empirically.

Our analysis is particularly relevant for recent macroeconomic models that relate FOMC policy to the output gap. For example, the framework in Campbell, Pflueger, and Viceira (2020) assumes that the log surplus consumption ratio 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 investigate this assumption by regressing the non-AR(1) component of our estimate of the log surplus consumption ratio on changes in lagged consumption growth, using the latter as a benchmark combination of output lags. While we do not find a significant statistical relationship between the two variables, using the point estimate from the regression implies plausible macroeconomic dynamics that are consistent with the approach in these models.

Although our findings are largely consistent with this type of preference specification, we note that the implications of the model are sensitive to variation in the forward- and backward-looking weights in the Euler equation. Our estimation approach allows these parameters to arise naturally, rather than assuming that the weights add up to one, as in some New Keynesian macroeconomic models. Nonetheless, the sum of the weights is very close to one by our estimation.

Our approach to estimating the relationship between the log surplus consumption ratio and output gap lags provides more accurate parameter estimates when the level of the surplus is close to its steady state. We find that the coefficient on the twice-lagged output gap (θ_2) is smaller (in absolute value) when the estimations exclude recessions from the sample. This implies that the backward-looking element of the Euler equation has a smaller impact outside of recessions.

Because our approach incorporates additional information from the corporate bond market, we are not compelled to calibrate the model to an existing estimate of the impact of monetary policy on output. Instead, we produce this impulse response function as a model output. We find that the calibration estimates are consistent with a dynamic macroeconomic model where a 100 basis point Fed Funds rate shock leads to a drop in output of -0.5% to -0.7%. The impulse response function associated with this set of parameters has the desired hump shape with a trough at five to eight quarters. The trough is further out when recession years are included in the estimation sample, reflecting their impact in raising the backward-looking coefficient in the Euler equation. Our range of estimates of the impact of monetary policy in output are similar to those of Christiano, Eichenbaum, and Evans (1999), and also those of Bernanke, Boivin, and Eliasz (2005).

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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

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

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

which implies the Euler equation (6) for real risk-free rates. Substituting (1), (2) and (3) into (6), and simplifying, gives

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

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

Substituting (5) into (A.1), and rearranging, yields

$$\begin{aligned}
r_t &= \gamma\mathbb{E}_t(x_{t+1}) - \gamma\phi x_t + \gamma\theta_1 x_t + \gamma\theta_2 x_{t-1} \\
&= \gamma\mathbb{E}_t(x_{t+1}) - \gamma(\phi - \theta_1)x_t + \gamma\theta_2 x_{t-1} \\
\gamma(\phi-\theta_1)x_t &= \gamma\mathbb{E}_t(x_{t+1}) + \gamma\theta_2 x_{t-1} - r_t \\
x_t &= \frac{1}{\phi-\theta_1}\mathbb{E}_t(x_{t+1}) + \frac{\theta_2}{\phi-\theta_1}x_{t-1} - \frac{1}{\gamma(\phi-\theta_1)}r_t.
\end{aligned}$$

A.2. Derivation of $\text{prem}_{Y+V_Y,t} = \beta_{Y,t}\,\text{prem}_t$

The tower property of conditional expectations gives

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

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

$$\text{prem}_{Y+V_Y,t} = -\text{Cov}_t\left(\frac{\exp(\Delta m_{t+1})}{\mathbb{E}_t(\exp(\Delta m_{t+1}))}, \frac{Y_{t+1}+V_{Y,t+1}}{\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})}\right). \tag{A.2}$$

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,

$$\begin{aligned}
\mathbb{E}_t(R_{Y,t+1}) - R_{f,t} &= \frac{\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})}{V_{Y,t}} - \frac{1}{\mathbb{E}_t(\exp(\Delta m_{t+1}))} \\
&= \frac{\mathbb{E}_t(\exp(\Delta m_{t+1}))\,\mathbb{E}_t(Y_{t+1}+V_{Y,t+1}) - V_{Y,t}}{V_{Y,t}\,\mathbb{E}_t(\exp(\Delta m_{t+1}))} \\
&= -\frac{\mathbb{E}_t(\exp(\Delta m_{t+1}))\,\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})\text{Cov}_t\left(\frac{\exp(\Delta m_{t+1})}{\mathbb{E}_t(\exp(\Delta m_{t+1}))}, \frac{Y_{t+1}+V_{Y,t+1}}{\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})}\right)}{V_{Y,t}\,\mathbb{E}_t(\exp(\Delta m_{t+1}))},
\end{aligned}$$

and thus

$$\frac{\mathbb{E}_t(R_{Y,t+1}) - R_{f,t}}{\mathbb{E}_t(R_{Y,t+1})} = -\text{Cov}_t\left(\frac{\exp(\Delta m_{t+1})}{\mathbb{E}_t(\exp(\Delta m_{t+1}))}, \frac{Y_{t+1}+V_{Y,t+1}}{\mathbb{E}_t(Y_{t+1}+V_{Y,t+1})}\right). \tag{A.3}$$

Equating (A.2) and (A.3) yields

$$\begin{aligned}
\text{prem}_{Y+V_Y,t} &= \frac{\mathbb{E}_t(R_{Y,t+1}) - R_{f,t}}{\mathbb{E}_t(R_{Y,t+1})} \\
&\approx 1 - \exp\left(-(\log(\mathbb{E}_t(R_{Y,t+1})) - r_{f,t})\right) \\
&\approx \log(\mathbb{E}_t(R_{Y,t+1})) - r_{f,t}.
\end{aligned}$$

Using (1), 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

$$\begin{aligned}
\frac{\exp(\Delta m_{t+1})}{\mathbb{E}_t(\exp(\Delta m_{t+1}))} &= \frac{\exp(-\gamma(\Delta c_{t+1}+\Delta s_{t+1}))}{\mathbb{E}_t(\exp(-\gamma(\Delta c_{t+1}+\Delta s_{t+1})))} \\
&= \exp\left(-\gamma(1+\lambda(s_t))\varepsilon_{c,t+1}-\frac{1}{2}\gamma^2(1+\lambda(s_t))^2\sigma_c^2\right) \\
&\approx 1-\gamma(1+\lambda(s_t))\varepsilon_{c,t+1}-\frac{1}{2}\gamma^2(1+\lambda(s_t))^2\sigma_c^2. \qquad \text{(A.4)}
\end{aligned}$$

Substituting (A.4) into (A.2) yields the approximate relationship

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

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 $Y_{t+1}+V_{Y,t+1}=C_{t+1}$,

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

Substituting (3) into (14), and considering cases where s_t is close to the steady state, we obtain

$$\begin{aligned}
\text{prem}_t &= \gamma\frac{1}{\bar{S}}\sqrt{1-2(s_t-\bar{s})}\sigma_c^2 \\
\log(\text{prem}_t) &= \text{constant}+\frac{1}{2}\log(1-2(s_t-\bar{s})) \\
&\approx \text{constant}+\frac{1}{2}\log[\exp(-2(s_t-\bar{s}))] \\
&= \text{constant}-s_t.
\end{aligned}$$

A.3. 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

$$
\begin{aligned}
B_{it} &= \mathbb{E}_t(\exp(\Delta m_{t+1})(1-L_{i,t+1})) \\
&= \mathbb{E}_t(\exp(\Delta m_{t+1}))\,\mathbb{E}_t(1-L_{i,t+1})\frac{\mathbb{E}_t(\exp(\Delta m_{t+1})(1-L_{i,t+1}))}{\mathbb{E}_t(\exp(\Delta m_{t+1}))\,\mathbb{E}_t(1-L_{i,t+1})} \\
&= \mathbb{E}_t(\exp(\Delta m_{t+1}))\,\mathbb{E}_t(1-L_{i,t+1})(1-\text{prem}_{1-L,it}),
\end{aligned}
$$

we obtain

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

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

$$
\widehat{s}_{it} - \mathbb{E}_t(L_{i,t+1}) = \mathbb{E}_t(1-L_{i,t+1})\,\text{prem}_{1-L,it}\,\ell_{it}, \tag{A.5}
$$

as modeled by ℓ_{it}. Applying the definition (A.2), Equation (A.5) implies

$$
\begin{aligned}
\frac{\widehat{s}_{it} - \mathbb{E}_t(L_{i,t+1})}{\mathbb{E}_t(L_{i,t+1})} &= \frac{\mathbb{E}_t(1-L_{i,t+1})}{\mathbb{E}_t(L_{i,t+1})}\beta_{1-L,it}\,\text{prem}_t\,\ell_{it} \\
&= -\frac{\mathbb{E}_t(1-L_{i,t+1})}{\mathbb{E}_t(L_{i,t+1})}\text{Cov}_t\left(\frac{\exp(\Delta m_{t+1})}{\mathbb{E}_t(\exp(\Delta m_{t+1}))}, \frac{1-L_{i,t+1}}{\mathbb{E}_t(1-L_{i,t+1})}\right)\text{prem}_t\,\ell_{it} \\
&= \text{Cov}_t\left(\frac{\exp(\Delta m_{t+1})}{\mathbb{E}_t(\exp(\Delta m_{t+1}))}, \frac{L_{i,t+1}}{\mathbb{E}_t(L_{i,t+1})}\right)\text{prem}_t\,\ell_{it} \\
&= -\beta_{L,it}\,\text{prem}_t\,\ell_{it}.
\end{aligned}
$$

B. Additional Tables and Figures

Table B.1: Predicting default rates

	Aa				A				Baa			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Const	-5.37	-5.46	-6.94	-6.74	-4.55	-4.57	-5.64	-5.24	-3.76	-3.80	-4.38	-3.94
	(0.06)	(0.08)	(0.10)	(0.10)	(0.06)	(0.07)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)	(0.04)
Ret		-0.14	0.42	0.56		-0.11	0.91	1.45		-0.33	0.58	1.15
		(0.21)	(0.11)	(0.14)		(0.23)	(0.16)	(0.21)		(0.25)	(0.22)	(0.24)
GDP			-2.33	-4.19			-7.82	-16.1			-8.13	-14.7
			(0.43)	(1.06)			(0.92)	(1.67)			(1.31)	(2.13)
Slope				3.59				-2.77				-9.69
				(1.02)				(1.86)				(1.93)
DR	0.46	0.42	0.09	0.12	1.05	1.02	0.32	0.41	2.27	2.15	1.07	1.37
RMSE	0.99	1.01	0.26	0.29	2.03	2.10	0.44	0.46	3.54	3.61	1.05	1.03
Obs	1,170	1,078	835	646	1,170	1,078	835	646	1,170	1,078	835	646

	Ba				B			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Const	-2.73	-2.71	-2.70	-2.30	-1.87	-1.87	-1.70	-1.22
	(0.03)	(0.03)	(0.05)	(0.05)	(0.03)	(0.03)	(0.06)	(0.04)
Ret		-0.79	0.30	1.13		-0.32	0.85	1.07
		(0.18)	(0.19)	(0.18)		(0.19)	(0.24)	(0.16)
GDP			-12.6	-24.1			-12.2	-17.3
			(1.77)	(2.34)			(1.94)	(2.10)
Slope				-3.23				-7.05
				(1.81)				(1.63)
DR	6.18	6.08	4.92	6.04	14.05	13.90	13.34	16.85
RMSE	6.33	6.47	4.39	4.34	11.09	11.49	9.83	8.32
Obs	1,170	1,078	835	646	1,170	1,078	835	646

This table reports the results for the rating-specific beta regressions of realized default rates on 12-month trailing equity index returns (Ret), predicted real GDP growth (GDP), and the difference between the ten-year and three-month Treasury rates (slope). The time periods underlying panels (1)–(4) start in May 1919, January 1927, April 1947 and January 1963, respectively, and each last through October 2016. The S&P 500 index is from CRSP, the predictions for real GDP growth are four-quarter-ahead consensus forecasts, and the slope data come from the Federal Reserve.

Table B.2: 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.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
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 US 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 are annualized and reported in basis points.

Table B.4: Correlations between risk premium measures

	Monthly					Quarterly				
	log(prem)	EBP	log(cs)	log(RA)	log(VIX)	log(prem)	EBP	log(cs)	log(RA)	log(VIX)
	1973.1–2021.9					**1973.I–2021.III**				
log(prem)						1				
EBP	0.76	1				0.78	1			
log(cs)	0.58	0.52	1			0.58	0.538	1		
	1973.1–2021.9					**1990.I–2021.III**				
log(prem)	1					1				
EBP	0.81	1				0.81	1			
log(cs)	0.70	0.66	1			0.70	0.65	1		
log(RA)	0.65	0.72	0.64	1		0.67	0.70	0.63	1	
log(VIX)	0.58	0.57	0.50	0.808	1	0.59	0.59	0.50	0.85	1

This table reports correlations between our market risk premium measure log(prem) and other related risk premium proxies. EBP is the excess bond premium from Gilchrist and Zakrajšek (2012), cs is the Baa-Aaa spread sourced from FRED, RA is the risk aversion variable in Bekaert, Engstrom, and Xu (2021), and VIX is the stock market volatility index disseminated by the CBOE.

Table B.5: Model input parameters

		Value	Source	Empirical target
Preferences				
Consumption growth	g	1.89	Campbell and Cochrane (1999)	Average consumption growth
Utility curvature	γ	2	Campbell and Cochrane (1999)	Equity Sharpe ratio
Steady-state risk-free rate	$\bar{r}$	0.94	Campbell and Cochrane (1999)	Average real risk-free rate
Persistence surplus cons.	θ_0	0.87	Campbell and Cochrane (1999)	AR(1) price-dividend ratio
Monetary policy				
MP coefficient output	γ_x	1.5	Taylor (1993)	Reduced-form regression
MP coefficient inflation	γ_π	0.5	Taylor (1993)	Reduced-form regression
MP persistence	ρ_i	0.80	Clarida, Gali, and Gertler (2000)	Reduced-form regression
Inflation				
PC backward coefficient	ρ_π	0.80	Fuhrer (1997)	Quarterly inflation persistence
PC slope	κ	0.0062	Hazell et al. (2022)	Regional inflation-unempl. slope
Consumption				
Cons.–output gap link	ϕ	0.93	Campbell, Pflueger, and Viceira (2020)	Corr(output gap, detrended cons.)
Asset prices				
Leverage	δ	0.67	Pflueger and Rinaldi (2022)	SD equity returns

Similar to Table 1 in Pflueger and Rinaldi (2022), this table reports the model parameter values, the articles that these parameter values are drawn from, and the empirical moments that the literature has targeted with these parameters. Consumption growth and the steady-state risk-free rate are in annualized percent. The monetary policy (MP) 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.

Table B.6: Fitting SD of monetary policy shocks

Panel A: 1973.I–2021.III *($\theta_1 = -1.47$, $\theta_2 = 1.37$, $\alpha = 0.99$)*

Free parameter											
σ_{MP}	1.75	1.76	1.77	1.78	1.79	1.80	1.81	1.82	1.83	1.84	1.85
Implied equity moments											
Equity premium	8.41	8.43	8.45	8.47	8.49	8.51	8.53	8.55	8.57	8.59	8.61
Volatility	17.23	17.27	17.32	17.36	17.40	17.45	17.49	17.53	17.58	17.62	17.66
Sharpe ratio	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49
Implied macroeconomic dynamics											
σ_c	1.47	1.48	1.49	1.50	1.51	1.52	1.52	1.53	1.54	1.55	1.56
σ_r	3.27	3.29	3.30	3.32	3.34	3.36	3.38	3.40	3.42	3.43	3.45
Trough magn. output	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55	-0.55
Lag trough (quarters)	8	8	8	8	8	8	8	8	8	8	8

Panel B: 1986.I–2021.III *($\theta_1 = -1.52$, $\theta_2 = 1.41$, $\alpha = 0.99$)*

Free parameter											
σ_{MP}	1.80	1.81	1.82	1.83	1.84	1.85	1.86	1.87	1.88	1.89	1.90
Implied equity moments											
Equity premium	8.52	8.54	8.56	8.58	8.60	8.62	8.64	8.66	8.68	8.70	8.72
Volatility	17.48	17.52	17.56	17.61	17.65	17.69	17.74	17.78	17.82	17.87	17.91
Sharpe ratio	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49
Implied macroeconomic dynamics											
σ_c	1.44	1.45	1.46	1.47	1.48	1.48	1.49	1.50	1.51	1.52	1.52
σ_r	3.36	3.38	3.40	3.42	3.43	3.45	3.47	3.49	3.51	3.53	3.55
Trough magn. output	-0.53	-0.53	-0.53	-0.53	-0.53	-0.53	-0.53	-0.53	-0.53	-0.53	-0.53
Lag trough (quarters)	8	8	8	8	8	8	8	8	8	8	8

Panel C: 1986.I–2021.III, excl. recessions *($\theta_1 = -1.03$, $\theta_2 = 0.95$, $\alpha = 1.00$)*

Free parameter											
σ_{MP}	1.10	1.11	1.12	1.13	1.14	1.15	1.16	1.17	1.18	1.19	1.20
Implied equity moments											
Equity premium	7.02	7.04	7.06	7.09	7.11	7.14	7.16	7.18	7.21	7.23	7.25
Volatility	14.30	14.35	14.40	14.45	14.49	14.54	14.59	14.64	14.69	14.73	14.78
Sharpe ratio	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49
Implied macroeconomic dynamics											
σ_c	1.44	1.45	1.46	1.48	1.49	1.50	1.51	1.53	1.54	1.55	1.57
σ_r	2.01	2.03	2.05	2.07	2.09	2.11	2.12	2.14	2.16	2.18	2.20
Trough magn. output	-0.74	-0.74	-0.74	-0.74	-0.74	-0.74	-0.74	-0.74	-0.74	-0.74	-0.74
Lag trough (quarters)	5	5	5	5	5	5	5	5	5	5	5

The table reports the model-implied macroeconomic dynamics and equity moments, as a function of the assumed standard deviation of monetary policy shocks σ_{MP}. The parameter θ_1 is estimated as in Table 3, and the model input parameters are from Table B.5.

Table B.7: Fitting SD of monetary policy shocks: EBP measure

***Panel A: 1973.I–2021.III** ($\theta_1 = -2.08$, $\theta_2 = 1.93$, $\alpha = 0.97$)*						
Free parameter						
σ_{MP}	0.50	1.00	1.50	2.00	2.50	3.00
Equity						
Equity premium	5.48	6.85	8.02	9.06	10.02	10.90
Volatility	11.10	14.00	16.49	18.79	20.95	23.03
Sharpe ratio	0.49	0.49	0.49	0.48	0.48	0.47
Implied macroeconomic dynamics						
σ_c	0.25	0.50	0.75	1.00	1.25	1.49
σ_r	0.93	1.86	2.78	3.71	4.64	5.57
Trough magn. output	-0.36	-0.36	-0.36	-0.36	-0.36	-0.36
Lag trough (quarters)	10	10	10	10	10	10
***Panel B: 1986.I–2021.III** ($\theta_1 = -3.10$, $\theta_2 = 2.89$, $\alpha = 0.96$)*						
Free parameter						
σ_{MP}	0.50	1.00	1.50	2.00	2.50	3.00
Equity						
Equity premium	5.55	6.97	8.17	9.25	10.23	11.12
Volatility	11.29	14.31	16.92	19.32	21.60	23.78
Sharpe ratio	0.49	0.49	0.48	0.48	0.47	0.47
Implied macroeconomic dynamics						
σ_c	0.15	0.29	0.44	0.58	0.73	0.87
σ_r	0.92	1.84	2.77	3.69	4.61	5.53
Trough magn. output	-0.22	-0.22	-0.22	-0.22	-0.22	-0.22
Lag trough (quarters)	13	13	13	13	13	13
***Panel C: 1986.I–2021.III, excl. recessions** ($\theta_1 = -1.18$, $\theta_2 = 1.10$, $\alpha = 0.99$)*						
Free parameter						
σ_{MP}	1.29	1.30	1.31	1.32	1.33	1.34
Equity						
Equity premium	7.41	7.44	7.46	7.48	7.50	7.53
Volatility	15.11	15.15	15.20	15.25	15.29	15.34
Sharpe ratio	0.49	0.49	0.49	0.49	0.49	0.49
Implied macroeconomic dynamics						
σ_c	1.47	1.48	1.49	1.50	1.51	1.53
σ_r	2.40	2.41	2.43	2.45	2.47	2.49
Trough magn. output	-0.68	-0.68	-0.68	-0.68	-0.68	-0.68
Lag trough (quarters)	6	6	6	6	6	6

The table reports the model-implied macroeconomic dynamics and equity moments, as a function of the assumed standard deviation of monetary policy shocks σ_{MP}. The parameter θ_1 is estimated as the coefficient in a regression of $-(\mathrm{EBP}_{t+1} - \theta_0 \mathrm{EBP}_t)$ on Δc_t, and the model input parameters are from Table B.5.

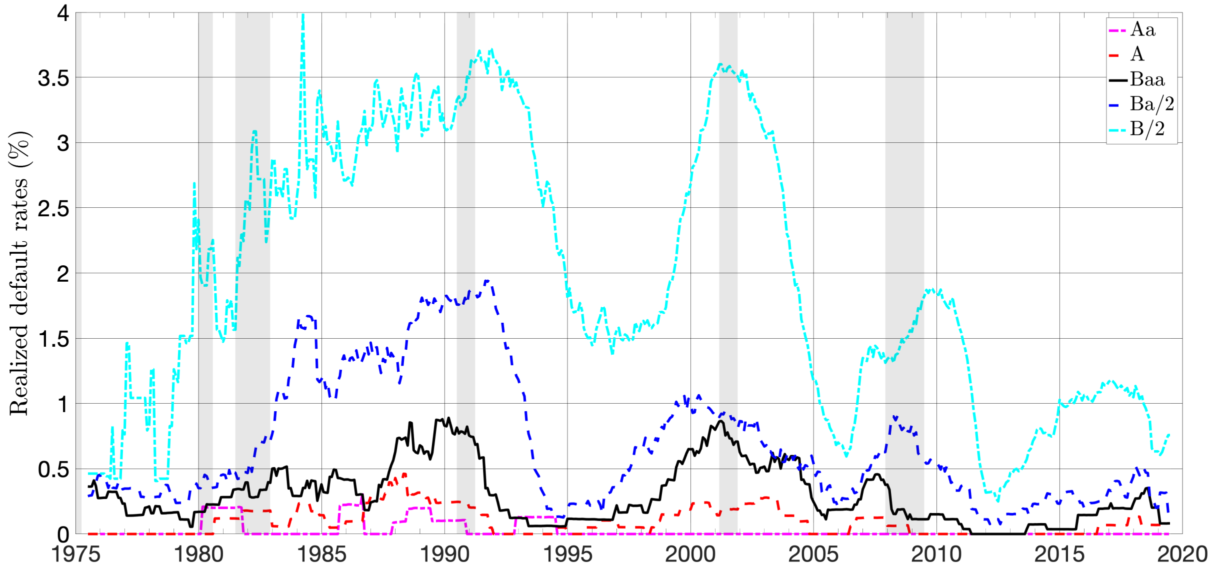

Figure B.1: Realized default rates

The figure shows the monthly times series of annualized five-year realized default rates by letter rating. 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 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.

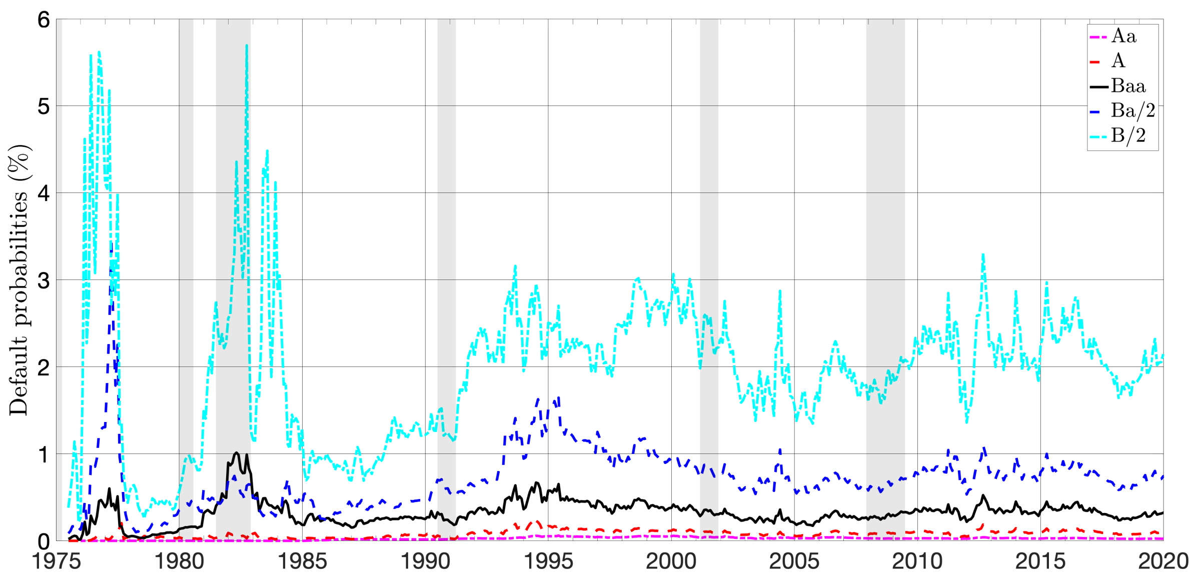

Figure B.2: Probabilities of default

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, CRSP, FRED and Gurkaynak, Sack, and Wright (2007). 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.