Does the Long-Run Risk Explain the Cross-Section of Corporate Bond Returns?[1]

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Abstract

We test whether long-run consumption risk can explain the cross-section of corporate bond risk premiums. We find that a one-factor model with long-run consumption growth explains the risk premiums on bond portfolios sorted on credit spreads, maturity, credit rating, downside risk, idiosyncratic volatility, and the betas with respect to shocks to financial intermediary's capital of He, Kelly, and Manela (2017). Furthermore, the estimated risk aversion coefficient declines as we increase the horizon to measure consumption growth, and a model with relatively low values of risk-aversion can match the observed risk premiums if we use 24-month growth rate as a risk factor.

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1 Introduction

Research on the cross-sectional determinant of risks and risk premiums on corporate bonds has grown substantially in recent years. Various characteristics of corporate bonds, such as credit spreads (Nozawa (2017)), credit rating, maturity (Gebhardt, Hvidkjaer, and Swaminathan (2005)), downside risk, liquidity (Bai, Bali, and Wen (2019)), momentum (Jostova et al. (2013)), and volatility (Chung, Wang, and Wu (2019)) are shown to predict bond returns. However, relatively few papers try to explain these cross-sectional variations in risk premiums using macroeconomic variables.

In this paper, we study whether the long-run risk model in the spirit of Bansal and Yaron (2004) explains the cross-sectional variation in corporate bond risk premiums or not. A priori, there are two reasons to conjecture that the long-run risk model explains bond risk premiums. First, there is evidence that the model works well in explaining the aggregate credit spreads (e.g. Bhamra, Kuehn, and Strebulaev (2010b) and Chen (2010)). Since credit spreads can be decomposed into risk premiums and expected losses, a model that explains credit spreads should also explain risk premiums on corporate bonds. We calibrate the model of Bhamra, Kuehn, and Strebulaev (2010b) and find that the model indeed generates large corporate bond risk premiums, and much of the premiums are due to the long-run consumption risk rather than short-run risk.

Second, Gilchrist and Zakrajšek (2012) empirically show that credit spreads are a strong predictor of economic growth. Specifically, a lower level of credit spreads is associated with higher economic growth in the near future. These results suggest that changes in credit spreads also predict future consumption growth. This predictability implies comovement between bond returns and expected consumption growth, which is the key source of risk that is priced in the long-run risk model. Indeed, in the data, we find robust evidence that corporate bond returns predict consumption growth rate over the next 24 months. Furthermore, returns on corporate bond portfolios with higher average returns predict consumption growth better than those with lower average returns. Therefore, with these theoretical and empirical motivations, we conjecture that the long-run risk model may explain cross-sectional variation in risk premiums on corporate bonds.

To formally test the long-run risk model, we follow Malloy, Moskowitz, and Vissing-Jørgensen (2009) in estimating the long-run risk model using 35 portfolios of corporate bonds sorted on credit spreads, credit rating, maturity, downside risk, idiosyncratic volatility, and the betas with respect to the intermediary asset pricing factor of He, Kelly, and Manela (2017) as well as 8 Treasury bond portfolios. We use the aggregate household consumption growth rate accumulated over 1 to 24 months as an asset pricing factor, and study whether this one-factor model explains the cross-sectional variation in bond risk premiums. To this end, we regress average bond returns on the covariance between cumulative consumption growth and bond returns, and estimate the risk aversion coefficient.

We find that the long-run risk model fits the data well, with the cross-sectional R-squared of 0.74 in the main specification. More importantly, we find that the risk-aversion coefficient decreases as we employ a risk factor based on consumption growth over the longer horizon. When we use monthly consumption growth as a risk factor, the risk aversion coefficient is estimated at 335, which is implausibly high. However, if we instead use 24-month cumulative consumption growth as a factor, the risk-aversion coefficient decreases to 43, which is much closer to what is used in the literature. The decrease in the estimated risk aversion coefficient highlights the importance of accounting for long-run consumption growth when measuring the quantity of risk for corporate bonds.

To measure consumption risk over the longer horizon than 24 months, we estimate a vector autoregression (VAR) involving consumption growth and the principal components of a large number of macrovariables, constructed following Ludvigson and Ng (2007). The estimated VAR enables us to calculate shocks to expected consumption growth over the infinite horizon, and estimate the long-run risk model using this shock as a risk factor. The one-factor model using shocks to the expected infinite horizon consumption growth yields a risk-aversion coefficient of 21 with cross-sectional R-squared of 0.78. This good performance of the model underscores the key finding in this article that measuring consumption growth over the long run helps the model to match the observed bond risk premiums with a more realistic risk aversion coefficient.

In evaluating the performance of the long-run risk model, we are mindful of the critique of Lewellen, Nagel, and Shanken (2010) on asset pricing tests. To this end, we form portfolios of corporate bonds using 6 sorting variables to break the factor structure in test asset returns. Furthermore, we treat the point estimates for the risk-aversion coefficient seriously and ensure that the estimates are in line with the value used in the literature. Finally, we calculate the confidence interval of the cross-sectional R-squared to ensure that the good fit of the model is not spurious.

Furthermore, we extend the empirical analysis by accounting for the skewed distribution of the test assets. Since corporate bonds are effectively a portfolio of a risk-free bond and a short position on a put option on the borrower's asset, bond returns are likely to be negatively skewed, invalidating the standard assumption of lognormality in estimating the Euler equation. We follow Harvey and Siddique (2000) and account for coskewness between long-run consumption growth and bond returns, and find that the results are largely consistent with our main results, though the estimated risk-aversion coefficients and cross-sectional R-squared are slightly lower.

Finally, in order to verify that our results are not driven by the particular choice of portfolios, we use individual corporate bonds for test assets rather than portfolios. When we use individual bonds, the estimates for risk premiums on test assets become less precise, but we find that the estimate for the risk-aversion coefficient is unchanged from the main results. This finding provides further support to our claim that observed variation in corporate bond risk premiums can be explained by exposure to long-run consumption shocks.

Our paper relates to the literature on the cross-section of corporate bond returns. Gebhardt, Hvidkjaer, and Swaminathan (2005), Jostova et al. (2013), Chordia et al. (2017), Choi and Kim (2018), and Chung, Wang, and Wu (2019) document different predictors of bond returns. In particular, papers closest to ours are He, Kelly, and Manela (2017) and Bai, Bali, and Wen (2019). Both papers present different factor models with different motivations to explain the cross-section of corporate bond returns. Our paper is complementary to those papers, as we use the same test assets as theirs, and offer a different explanation for the risk premiums using the long-run risk model. Importantly, in our baseline specification, our model uses aggregate household consumption growth rate as an only risk factor, and thus we offer a more parsimonious explanation of risk premiums based on fundamentals than these papers do.

There is another strand of literature which incorporates macroeconomic factors in structural models of debt to price corporate credit spreads. Chen, Collin-Dufresne, and Goldstein (2008), Bhamra, Kuehn, and Strebulaev (2010b), Chen (2010), and Elkamhi, Jo, and Salerno (2020) calibrate consumption-based models to explain the aggregate credit spreads. Our paper differs because we examine the heterogeneity among corporate bonds, and focus on risk premiums rather than credit spreads.

Our paper also contributes to the literature that investigates the link between slow-moving components in consumption growth and cross-section of asset returns, including Hansen, Heaton, and Li (2008), Malloy, Moskowitz, and Vissing-Jørgensen (2009), Bansal, Kiku, and Yaron (2009), and Elkamhi and Jo (2019). Bryzgalova and Julliard (2019) show that stocks and Treasury bond returns predict future consumption growth. We complement their findings by showing that corporate bond returns also predict future consumption growth.

The rest of the paper is organized as follows: in Section 2, we present the long-run risk model and show that theoretically, the model is capable of generating realistic risk premiums for different types of bonds; in Section 3, we discuss data and the empirical application of the long-run risk model; in Section 4, we present the empirical results; in Section 5, we present several extension of the empirical analysis; and in Section 6, we provide concluding remarks.

2 Theoretical motivation

Recent equilibrium-based structural models of credit risk (e.g. Bhamra, Kuehn, and Strebulaev, 2010a,b; Chen, 2010; Elkamhi, Jo, and Salerno, 2020) show that the long-run risk combined with recursive preferences well explains credit spreads. They do so by generating a large and negative covariance between the pricing kernel and cash flow. Since credit spreads contain at least two components which are expected losses and bond risk premiums, this finding in the literature suggests that the long-run risk may have the ability to explain bond risk premiums as well. While those models study credit spreads, in this section, we focus on the bond risk premiums in particular. We examine the contribution of the long-run risk to the total bond risk premiums to motivate our choice of the long-run risk model. The model of Bhamra, Kuehn, and Strebulaev (2010b) is a natural choice for this exercise because, in their model, the long-run risk is incorporated into a structural model in a parsimonious way through two states regime change of the economy where one can identify the marginal effect of the long-run risk. Specifically, we quantify the relative importance of the long-run risk for the bond risk premiums. Our next calibration result shows that the long-run risk is responsible for 94% to 102% of the bond risk premiums. This finding lends theoretical support to our choice of the long-run risk model to price corporate bonds.

2.1 Model

We adapt the model developed by Bhamra, Kuehn, and Strebulaev (2010b). The key assumptions of the model are the time-varying first and second moments of corporate earnings and consumption growth combined with recursive preferences. The state of the economy slowly changes according to a two-state Markov chain, and the state determines the level of the first and second moments of earnings and consumption growth. In this setup, the long-run consumption risk arises from the macroeconomic uncertainty together with a representative agent's preference for the early resolution of uncertainty that stems from a higher risk aversion than the reciprocal of the elasticity of intertemporal substitution (EIS). We refer to Appendix A.1 for more details on the model.

2.2 Calibration

This subsection presents the calibration of the model. We use the same parameter values as in Bhamra, Kuehn, and Strebulaev (2010b). They use aggregate U.S. consumption and corporate earnings data from 1947Q1 to 2005Q4 to estimate parameter values. Table A.1 summarizes parameter values for our calibration. Although the model of Bhamra, Kuehn, and Strebulaev (2010b) allows for time-varying volatility of consumption growth and earnings growth, we impose constant volatility in order to be consistent with the model of Hansen, Heaton, and Li (2008) and Malloy, Moskowitz, and Vissing-Jørgensen (2009), which we build upon for our empirical analysis.[2] For the same reason, as in these papers

[2]To impose constant volatility, we fix the volatility of consumption and earnings growth to the long-run average of state-dependent volatilities, which are given in Bhamra, Kuehn, and Strebulaev (2010b).

and our empirical setting, we set the EIS to be one. As for the coefficient of relative risk aversion, we use risk aversion equal 10 as in Bansal and Yaron (2004) and Bhamra, Kuehn, and Strebulaev (2010b). Setting the coefficient of risk aversion greater than the reciprocal of the EIS ensures that the representative agent has a preference for early resolution of uncertainty, and thus she is averse to long-run risk.

Our main focus is to assess the relative importance of the long-run risk component for the bond risk premiums. To this end, we first measure total risk premiums with both short- and long-run risk components with state-dependent expected consumption and earnings growth rate. Next, we obtain the short-run component by eliminating the macroeconomic uncertainty. Finally, we quantify the long-run risk component by subtracting the short-run risk component from the baseline case where both short- and long-run risks are present. More specifically, to eliminate the macroeconomic uncertainty, we impose the state-*independent* expected consumption and earnings growth rate.[3] To measure the bond risk premiums, we subtract expected loss spreads (spreads computed using P default probabilities as in Du, Elkamhi, and Ericsson (2019)) from total spreads.

First, our model calibration generates empirically observed levels of equity risk premium of 2.69%[4] and credit spread of 71 basis points, for a market leverage ratio of 40%. Also, the bond risk premium is 37 basis points and the expected loss is 34 basis points, which reasonably matches the empirical counterpart. The total bond risk premium of 37 basis points is decomposed into 35 basis points that stems from the long-run risk component and the remaining 2 basis points from the short-run risk component. Therefore, the long-run risk component accounts for nearly a hundred percent of the risk premiums. Next, in order to study how the relative importance of the long-run risk component depends on the level of the leverage ratio, we exogenously vary the leverage ratio from 10% to 80%. Panel A of Figure 1 shows the result.[5] The contribution of the long-run risk to bond risk premiums ranges from 94% to 102%. Hence, the long-run risk explains nearly a hundred percent of bond

[3]We confirm that in this case, the size of the jump in the state-price density in terms of ratio equals one.

[4]This is the same as 2.69% in Bhamra, Kuehn, and Strebulaev (2010b) for average firms with the no-refinancing and default case.

[5]We do the same calibration exercise for equity, and find that the contribution of the the long-run risk for equity is slightly lower than for bond. The result is in Figure A.1.

risk premiums regardless of the level of the leverage ratio. Moreover, although both short- and long-run risk components increase with the leverage ratio due to higher default risk, the short-run risk component increases relatively more than the long-run risk component. Hence, the long-run risk plays a larger role in explaining the bond risk premiums when the leverage ratio is low, although the proportion of the long-run component changes negligibly across different leverage ratios. This is consistent with the recent equilibrium-based structural models (e.g. Bhamra, Kuehn, and Strebulaev, 2010a,b; Chen, 2010; Elkamhi, Jo, and Salerno, 2020) showing that the long-run risk can generate a large quantity of risk to explain the credit spread puzzle, especially for high credit quality firms where the puzzle is more severe.

To gain further insight into the importance of the long-run risk for bond risk premiums, we also conduct the comparative static analysis in terms of the convergence rate to long run. A higher convergence rate indicates faster news arrival, which implies a lower degree of persistence, and therefore lower long-run risk. We vary the convergence rate from 0.5646 to 0.9646 (0.7646 for the baseline) with the fixed leverage ratio of 40%. Panel B of Figure 1 shows that the long-run risk component decreases with the convergence rate, and also, not surprisingly, the relative importance of the long-run risk component decreases from 96% to 92% due to a lower long-run risk. However, throughout the range of convergence rate that we consider, the long-run risk always contributes more than 90%. Finally, we also vary the coefficient of risk aversion from 5 to 15 with the fixed leverage ratio of 40% and assess the importance of the long-run risk. Panel C of Figure 1 shows that the contribution of the long-run risk component to the bond risk premiums is not sensitive to the levels of risk aversion, ranging from 93% to 95%. These comparative static analysis results illustrate the robustness of the long-run risk in generating large bond risk premiums.

Overall, our finding theoretically highlights the importance of the long-run aggregate consumption risk not only for credit spreads, which are well-known in the literature, but also for the bond risk premiums as well. This finding is robust to different levels of the leverage ratio, convergence rate, and risk aversion. This theoretical evidence provides a strong justification for why the long-run risk model is a natural choice to explain the cross-sectional returns of corporate bonds.

3 Data and methodology

3.1 Data

In this section, we describe data sets for the empirical analysis. We compute aggregate consumption growth rates using seasonally-adjusted monthly real personal consumption expenditures for nondurables and services from NIPA Table 2.8.3 from April 1962 to December 2018. The sample period is determined by the availability of instrument variables for the VAR estimation. Real per capita growth rates are calculated by deflating values in 2012 dollars and subtracting the log population growth rate, using monthly population from NIPA Table 2.6.

For data on corporate bond returns, we follow Nozawa (2017). We construct the panel data of corporate bond prices from the Lehman Brothers Fixed Income Database, the Mergent FISD/NAIC Database, TRACE, and DataStream. When there are overlaps among the four databases, we prioritize in the following order: the Lehman Brothers Fixed Income Database, TRACE, Mergent FISD/NAIC, and DataStream.

We remove bonds with floating rates and with option features other than callable bonds. Until the late 1980s, very few bonds were non-callable, and thus removing callable bonds would significantly reduce the length of the sample period. Crabbe (1991) estimates that call options contribute nine basis points to the bond spread, on average, for investment-grade bonds. Therefore, the effect of call options does not seem large enough to significantly affect our results.

We apply three filters to remove the observations that are likely to be subject to erroneous recording. First, we remove the price observations that are below 5 dollars or above 1,000 dollars per 100 dollar face value. Second, we remove bonds maturing in less than a year. Third, we remove the return observations that show a large bounce-back. Specifically, we compute the product of the adjacent return observations and remove both observations if the product is less than -0.04.

Using this panel data of corporate bonds, we form 6 sets of portfolios. First, Nozawa (2017) shows that credit spreads are a strong predictor of the cross-section of corporate bond returns. He, Kelly, and Manela (2017) test their intermediary asset pricing model using 10 portfolios sorted on credit spreads. Therefore, we use the same test assets for our analysis. Namely, once every year, we form 10 value-weighted portfolios based on the average credit spreads between month $t-12$ and $t-1$. We sort bonds in month t, and record the returns from month $t+1$ to $t+12$, when we rebalance. We put a one month lag between the period we observe credit spreads and the portfolio formation month to ensure that measurement errors in bond prices do not drive return predictability.

Next, we form portfolios sorted on credit risk, downside risk, maturity, and idiosyncratic volatility. Bai, Bali, and Wen (2019) sort bonds based on credit rating and downside risk (measured as the 5% VaR for bond returns over the past 36-month horizon[6]) and find that these characteristics are a strong predictor of corporate bond returns. Thus, we follow their methodology to form value-weighted portfolios. Furthermore, Gebhardt, Hvidkjaer, and Swaminathan (2005) use bond's maturity as a predictor variable, while Chung, Wang, and Wu (2019) use idiosyncratic volatility of bond returns.[7] Thus, every month, we double-sort bonds into 25 bins based on i) credit rating and downside risk, ii) credit rating and maturity, and iii) credit rating and idiosyncratic volatility. For each downside risk, maturity and idiosyncratic volatility quintile, we take a simple average across credit rating portfolios to form 5 downside risk-sorted portfolios, 5 maturity-sorted portfolios, and 5 idiosyncratic volatility portfolios. Separately, we form 5 value-weighted portfolios sorted on credit ratings.[8]

Furthermore, we examine whether the long-run risk model can price the return spreads created by the intermediary asset pricing model of He, Kelly, and Manela (2017). To this end, we estimate corporate bond betas against shocks to the intermediary's capital on the rolling 12-month windows.[9] We then sort bonds every month into 5 value-weighted port-

[6]We impose the minimum number of observation of 24 months.

[7]To compute idiosyncratic volatility, we run regressions of bond returns on the 5 factors of and Fama and French (2015) as well as innovation to VIX over the 36-month rolling window, and calculate the standard deviation of the regression residuals.

[8]Bai, Bali, and Wen (2019) also use portfolios sorted on liquidity and short-term reversals. Though liquidity is an important determinant for corporate bond risk premiums, we do not use these characteristics in the main test, as liquidity data is available only after July 2002 when TRACE data starts. We do not use short-term reversal either, as consumption-based models are not supposed to explain the market microstructure noise driving the short-term reversal.

[9]We also estimate the betas over the 36-month rolling windows, but this method does not lead to a significant difference in average returns between the first and last quintiles, and thus we use the portfolios based

folios based on the pre-formation betas. Following He, Kelly, and Manela (2017), we add 8 Treasury bond portfolios with a maturity of 3 months, 1, 2, 5, 7, 10, 20 and 30 years from CRSP as additional test assets.

To summarize, we have 10 corporate bond portfolios sorted on credit rating or maturity from February 1973 to June 2017, 10 portfolios sorted on credit spreads from February 1974 to June 2017, 10 portfolios sorted on downside risk and idiosyncratic volatility from February 1975 to June 2017, 5 portfolios sorted on intermediary factor betas from February 1976 to June 2017, and 8 government bond portfolios from February 1973 to June 2017.

Table 1 presents the summary statistics for corporate bond returns (Panel A) and consumption (Panel B). In Panel B, the standard deviation of monthly consumption growth is 0.32%, while the standard deviation of cumulative 24-month consumption growth is 2.04%. If future consumption growth comoves with current returns, then long-run consumption growth can generate greater covariance with current returns than contemporaneous consumption growth does. We confirm that this is the case in Section 4.

3.2 Methodology

We follow Malloy, Moskowitz, and Vissing-Jørgensen (2009) in estimating the long-run risk model. In the model, the representative agent in the economy has recursive preference of a form,

$$V_t = \left[(1-\delta) C_t^{1-\frac{1}{\rho}} + \delta \left[E_t(V_{t+1}^{1-\gamma}) \right]^{\frac{1-\frac{1}{\rho}}{1-\gamma}} \right]^{\frac{1}{1-\frac{1}{\rho}}}, \tag{1}$$

where C_t is consumption in month t, ρ is the elasticity of intertemporal substitution (EIS), γ is a risk-aversion coefficient, and δ is a subjective discount rate.

We assume that log consumption growth $c_{t+1} - c_t$ follows a stationary first-order vector-auto regression (VAR),

$$c_{t+1} - c_t = \mu_c + U_c x_t + \eta_0 w_{t+1}, \tag{2}$$

$$x_{t+1} = G x_t + H w_{t+1}. \tag{3}$$

where $c_t = \log C_t$, x_t is a vector of a state variable that predicts consumption growth, w_t is a vector of i.i.d. Normal random variables with mean zero and covariance matrix

on 12-month rolling window betas as our main results.

Σ. Eq. (2) and (3) imply that log consumption growth can be expressed as a stationary moving-average process of the form,

$$c_{t+1} - c_t = \mu_c + \sum_{s=0}^{\infty} \eta_s w_{t-s} \equiv \mu_c + \eta(L) w_t. \tag{4}$$

As Hansen, Heaton, and Li (2008) and Malloy, Moskowitz, and Vissing-Jørgensen (2009), we focus on a special case in which EIS is one. This assumption considerably simplifies the stochastic discount factor derived from the preference in (1). Under this assumption, the log stochastic discount factor is,

$$s_{t+1} = \log\delta - [\mu_c + \eta(L)w_{t+1}] + (1-\gamma)\eta(\delta)w_{t+1} - \frac{1}{2}(1-\gamma)^2\eta(\delta)^2, \tag{5}$$

$$= \log\delta - [c_{t+1} - c_t] + (1-\gamma)\left[(E_{t+1} - E_t)\sum_{s=0}^{\infty}\delta^s(c_{t+1+s} - c_{t+s})\right] - \frac{1}{2}(1-\gamma)^2\eta(\delta)^2, \tag{6}$$

$$\approx \log\delta + (1-\gamma)\left[(E_{t+1} - E_t)\sum_{s=0}^{\infty}\delta^s(c_{t+1+s} - c_{t+s})\right] - \frac{1}{2}(1-\gamma)^2\eta(\delta)^2. \tag{7}$$

In the last line, we drop the contemporaneous consumption growth $c_{t+1} - c_t$ because it is known that contemporaneous consumption growth plays little role in explaining asset returns (e.g. Malloy, Moskowitz, and Vissing-Jørgensen (2009)). The second term in the last line is the source of a shock to the stochastic discount factor: it captures the shock to investor's expectations for the future consumption growth rate. With the Epstein-Zin preference, such a shock affects investors' marginal utility of consumption in a month $t+1$, and thus should be reflected in asset prices.

With a valid stochastic discount factor, the Euler equation $E[S_{t+1}R_{i,t+1}] = 1$ must hold for any asset returns. In the main analysis, we make an additional assumption that a return $R_{i,t+1}$ is lognormally distributed. Thus, we derive the unconditional Euler equation for a log return on asset i in excess of the risk-free rate of return,

$$E[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} = -Cov(s_{t+1}, r_{i,t+1} - r_{f,t}). \tag{8}$$

We plug the log stochastic discount factor in (7) into (8) and obtain,

$$
\begin{aligned}
& E[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} \\
& \approx (\gamma - 1)cov\left((E_{t+1} - E_t)\sum_{s=0}^{\infty} \delta^s (c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}\right), \qquad (9) \\
& = (\gamma - 1)cov\left(\sum_{s=0}^{\infty} \delta^s (c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}\right) \\
& - (\gamma - 1)cov\left(E_t \sum_{s=0}^{\infty} \delta^s (c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}\right). \qquad (10)
\end{aligned}
$$

where $r_{i,t+1}$ is a monthly log return on an asset i, and $r_{f,t}$ is the risk-free rate. In the last line, we use the law of iterated expectations to remove E_{t+1}. We use an annual discount rate of 5%, which leads to $\delta = 0.95^{1/12}$.

Malloy, Moskowitz, and Vissing-Jørgensen (2009) test a simplified version of the Euler equation in (10) by dropping the second term that captures conditional expectation for consumption growth. In this case, expected log excess returns on an asset are given by their covariance with unconditional long-run consumption growth:

$$
\begin{aligned}
& E[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} \\
& \approx (\gamma - 1)cov\left(\sum_{s=0}^{\infty} \delta^s (c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}\right). \qquad (11)
\end{aligned}
$$

Eq. (11) highlights the importance of predictability of consumption growth. For the model to generate large risk premiums with a low risk aversion coefficient γ, an excess return on a bond in month $t+1$ must predict consumption growth in the future well, such that the covariance term in (11) is large. With the unconditional model in (11), we can directly test whether bond returns predict consumption growth by running predictive regression, which we turn to in the next section.

Malloy, Moskowitz, and Vissing-Jørgensen (2009) truncate the summation over the infinite horizon in (11) up to S months, replacing $\sum_{s=0}^{\infty} \delta^s (c_{t+1+s} - c_{t+s})$ with $\sum_{s=0}^{S-1} \delta^s (c_{t+1+s} - c_{t+s})$. Though this procedure involves an approximation, it has an advantage of transparency. If we test (10), we have to specify a VAR by taking a stand on the set of state variables that predict consumption growth and on their dynamics. In such cases, the empirical results inevitably depend on VAR specification and will be affected by estimation errors in VAR. The simplified model in (11) requires no VAR estimates since it only depends on the covariance between consumption growth and asset returns in the data. However, the simplified model has a limitation on how far we can extend the horizon S due to the limited sample size. To strike a balance between simplicity and accuracy, we first test the simplified unconditional model in (11) with finite S. We then present the conditional model in (10) that captures shocks to expected consumption growth over the infinite horizon.

4 Empirical results

4.1 Measuring long-run consumption risk

In order to test the Euler equation in (11), we measure the long-run consumption risk of corporate bond portfolios using the covariance between long-run consumption growth and monthly returns on bond portfolios.

To better understand the estimated quantity of risk, we split the covariance into the long-run and short-run components,

$$Cov\left(\sum_{s=0}^{S-1}\delta^s(c_{t+s+1}-c_{t+s}), r^e_{i,t+1}\right) = \underbrace{Cov\left(c_{t+1}-c_t, r^e_{i,t+1}\right)}_{\text{Short run}} + \underbrace{Cov\left(\sum_{s=1}^{S-1}\delta^s(c_{t+s+1}-c_{t+s}), r^e_{i,t+1}\right)}_{\text{Long run}}. \quad (12)$$

where $r^e_{i,t+1} = r_{i,t+1} - r_{f,t}$.

The short-run component corresponds to contemporaneous covariance between consumption growth and returns, which would be the only source of priced risk for a model with power utility households (e.g. Lucas (1978)). The long-run component of the covariance comes from the predictability of future consumption growth with bond returns. If a higher return in a month $t+1$ predicts higher consumption growth afterwards, then this long-run component is positive. In the language of the long-run risk model, the long-run component captures the comovement between bond returns and (time-varying) expected consumption growth rate. In the model, shocks to expected consumption growth carry a large price of risk and thus covariance between asset returns and these shocks generates large risk premiums. Therefore, the key empirical question is whether bond returns predict consumption growth or not and whether bonds with high average returns predict consumption more than bonds with low average returns.

Table 2 presents the estimated covariance between bond portfolio returns and long-run consumption growth with $S = 24$, together with the average monthly returns in excess of T-bill rates on the bond portfolios. Panel A of Table 2 reports the results for the portfolios sorted on credit spreads. As in Nozawa (2017), the average excess returns increase almost monotonically from the lowest decile (0.19%) to the highest decile (0.62%), implying that credit spreads are a predictor of the cross-section of bond returns. The estimated covariance between bond returns and contemporaneous consumption growth is mostly zero for all portfolios. In contrast, the covariance between bond returns and long-run consumption growth is generally large, and rises monotonically from the first decile (0.0026) to the last decile (0.0087), showing that high credit spread bonds predict long-run consumption growth better than low credit spread bonds do. Thus, the variation in consumption predictability across portfolios matches the variation in average excess returns.

The last six panels of Table 2 present similar results using the corporate bond portfolios sorted on downside risk, bond's maturity, credit rating, idiosyncratic volatility, and betas with respect to the intermediary leverage factor of He, Kelly, and Manela (2017) as well as Treasury bond portfolios. For all sorting variables, the long-run risk model generates the same pattern in covariance as that in average excess returns. Specifically, the covariance with 24-month consumption growth increases nearly monotonically from the first quintile to the last quintile for all portfolios. The average excess returns for those portfolios increase similarly, suggesting that the long-run risk model not only generates large risk exposures, but also the pattern in risk exposure which matches that in average excess returns.

Overall, we find empirical support for strong comovement between bond returns and expected consumption growth, the key source of priced risk in the long-run risk model. Therefore, the long-run risk model is a promising candidate to explain risk premiums on corporate bond returns. However, Lewellen, Nagel, and Shanken (2010) argue that finding a good cross-sectional fit does not necessarily provide a reliable evaluation of an asset pricing model. For a model to be valid, we should ensure that the estimated risk-aversion coefficient, γ, is within a reasonable range, and consistent with the previous literature. Thus, in the next section, we estimate γ using GMM framework, and formally evaluate the asset pricing model in (11).

4.2 Fit of the long-run risk model

In this section, we estimate the parameters of the long-run risk model in (11), and evaluate the performance of the model in explaining cross-section of corporate bond premiums. Specifically, we follow Malloy, Moskowitz, and Vissing-Jørgensen (2009) and use the GMM framework to simultaneously estimate covariance between long-run consumption growth and asset returns and model parameters. [10] For the test assets, we use 35 corporate bond portfolio returns including 10 credit spread-sorted portfolios, 5 downside risk-sorted portfolios, 5 maturity-sorted portfolios, 5 rating-sorted portfolios, 5 idiosyncratic volatility-sorted portfolios, and 5 intermediary beta-sorted portfolios, as well as 8 Treasury bond portfolios sorted on maturity. Given the critique of Lewellen, Nagel, and Shanken (2010), it is important to include multiple test assets in the test to break a tight factor structure in returns on the test assets; if we include only one set of portfolios based on a univariate sort, then the resulting cross-sectional fit can be mechanical. By including 6 sorting variables to sort corporate bonds, we provide a valid testing ground for the long-run risk model.

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[10] The GMM moment conditions are

$$E\left[\begin{array}{c} r_{i,t+1} - r_{f,t} + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} - \zeta - (\gamma - 1)\varepsilon_{c,t\to t+S}\,(r_{i,t+1} - r_{f,t}) \\ \varepsilon_{c,t\to t+S} \end{array}\right] = 0, \tag{13}$$

where $\varepsilon_{c,t\to t+S} = \sum_{s=0}^{S}\delta^s(c_{t+1+s} - c_{t+s}) - \mu_{\sum_{s=0}^{S}\delta^s(c_{t+1+s}-c_{t+s})}$, $\theta = \left(\begin{array}{ccc}\zeta & \gamma & \mu_{\sum_{s=0}^{S}\delta^s(c_{t+1+s}-c_{t+s})}\end{array}\right)$ are the parameters to be estimated. Since there are 44 moment conditions in total and three free parameters, the GMM procedure finds the best parameters to minimize the sum of squared moments:

$$\min_{\theta} g_T(\theta)' W g_T(\theta) \tag{14}$$

where $g_T(\theta)$ is the sample counterpart of the moments in (13), and W is the weighting matrix defined by,

$$W = \left(\begin{array}{cc} I_{43} & 0 \\ 0 & H \end{array}\right), \tag{15}$$

where we set H to be the number of test assets, which is sufficiently large to ensure that the mean of long-run consumption growth rate is well measured.

Then we run cross-sectional regressions,

$$\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} = \zeta + (\gamma - 1)\hat{\sigma}_{i,c} + e_i, \tag{16}$$

$$\hat{\sigma}_{i,c} = \hat{cov}\left(\sum_{s=0}^{S} \delta^s (c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}\right), \tag{17}$$

where $r_{i,t+1}$ is a monthly log return on an asset i, and $r_{f,t}$ is the log 30-day T-bill rate. To evaluate the fit of the model, we define the cross-sectional R-squared by $\bar{R}^2 = 1 - \frac{Var(\hat{E}[R_i^e] - \hat{R}_i^e)}{Var(\hat{E}[R_i^e])}$, where $\hat{E}[R_i^e] = E[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2}$, and $\hat{R}_i^e$ is the fitted value. To calculate the standard errors and 95% confidence interval for estimates and $\bar{R}^2$, we conduct bootstrap simulations by randomly drawing months with replacement 5,000 times, which accounts for the cross-sectional correlation in asset returns.[11]

Table 3 presents the estimated coefficients in (16) and cross-sectional R-squared with different values of S. When $S = 1$ month, we effectively ignore the long-run risk and only calculate the covariance between monthly returns and contemporaneous consumption growth. In this case, the estimated γ is 335, which is too high compared with the literature on the long-run risk model (e.g. Bansal and Yaron (2004)). Even though the fit of the model is reasonable with $\bar{R}^2 = 0.53$, a good fit with an implausible preference parameter suggests that we may be over-fitting the model to data, and $\bar{R}^2$ may not represent the true performance of the model.

The third to last columns in Table 3 show the estimates in (16) with different values of S. We find that, as S increases, the estimated risk-aversion parameter decreases. When $S = 3$, estimated γ goes down to 196, and when $S = 24$, estimated γ further decreases to 43. These results suggest that bond returns predict consumption growth better over a longer horizon, which leads to a greater quantity of risk. As a result, the estimated risk-aversion decreases monotonically as we increase S up to 24 months. However, extending S to 36

[11] The stationary bootstrap procedure introduced by Politis and Romano (1994) is used with the random block lengths drawn from a geometric distribution to ensure the stationarity of the resulting time-series. Specifically, we resample blocks of asset returns, risk-free rate, and the long-run risk measures randomly with replacement until the bootstrap sample size is equal to the number of real data observations. Then, we obtain estimates and $\bar{R}^2$ by re-running the regression using the bootstrap samples. We repeat this procedure 5,000 times and construct the bootstrap distribution of estimates and $\bar{R}^2$. To choose the expected block length, we follow Politis and White (2004) and set the optimal expected block length.

months does not reduce the estimated γ any more. Still, $S = 24$ or $S = 36$ is much shorter than infinity, which is the horizon suggested by the long-run risk model. Since our sample size is not large enough to further increase S and obtain reliable parameter estimates, we have to rely on a VAR to extend the horizon further. We turn to this issue in Section 4.3.

We next examine the regression intercept in (16). When we use $S = 24$, the estimated intercept term ζ is 0.09% per month, which is statistically indistinguishable from zero. This is important since the non-zero intercept would imply that the model misprices the risk-free asset. Given our estimate for the intercept is close to zero, our results do not suffer from the issue of a mispriced risk-free rate which is common in macro-finance literature. With $S = 24$, the cross-sectional R-squared is 0.74, which is large given that we use a one-factor model, and is significant when compared with the results in Malloy, Moskowitz, and Vissing-Jørgensen (2009).[12]

A consistent estimator of the risk aversion coefficient γ can also be obtained by running the cross-sectional regression in (16) in reverse,

$$\hat{\sigma}_{i,c} = \eta + \frac{1}{\gamma - 1}\left(\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2}\right) + u_i. \tag{18}$$

(16) and (18) generally yield different estimates for γ in sample, and thus we check if the estimated risk-aversion does not depend on our choice of estimation procedure.

Panel B of Table 3 reports the estimates for γ and the cross-sectional R-squared for (18). We find that estimated γ is decreasing in consumption horizon S with this alternative set of estimates, confirming the main results. The point estimates for γ are somewhat greater than the main results, but the cross-sectional R-squared remains unchanged.

Furthermore, we examine if the long-run risk model prices each set of portfolios consistently with each other. He, Kelly, and Manela (2017) emphasize that their intermediary leverage factor produces the estimated price of risk that are consistent across various asset classes, and declare a success because of this consistency. To examine the performance of the long-run risk model from this perspective, we separately estimate (13) using six subsam-

[12] Malloy, Moskowitz, and Vissing-Jørgensen (2009) report the R-squared of 0.65 for the size and book-to-market sorted portfolios using 24-month shareholder consumption growth, and 0.53 using 24-month top shareholder consumption growth (see their Table II).

ples of portfolios sorted on credit spreads, downside risk, maturity, credit rating, idiosyncratic volatility, and intermediary betas. Since each subsample has only 5 or 10 portfolios, the risk aversion parameter will not be as precisely estimated as before. Nonetheless, we conduct the analysis with $S = 24$, and report the results in Table 4.

Table 4 shows that, once we estimate the Euler equation separately, the estimated γ is 53 for credit spread portfolios, 78 for downside risk portfolios, 33 for maturity portfolios, 52 for credit rating portfolios, 42 for intermediary beta portfolios, 60 for idiosyncratic volatility portfolios, and 103 for Treasury bond portfolios. The two standard error bounds for these estimates include 43 from the main results in Table 3. Therefore, the estimated risk aversion is consistent across different test assets, though the measurement errors for subsamples are large.

Figure 2 shows the fit of the model graphically by comparing the predicted expected returns and the average excess returns in the data, using both full samples and seven subsamples of bond portfolios. If the model performs well, then we expect that observations line up along the 45-degree line. In the figure, the observations lie close to the 45-degree line for most subportfolios. A notable exception is the fifth quintile of downside-risk sorted portfolios which has higher average excess returns than the model's prediction. Because of this somewhat anomalous portfolio, the estimated γ using downside risk-sorted portfolios is higher than the results using all portfolios. However, overall results support the performance of the long-run risk model which generates mostly consistent γ across different test assets.

4.3 Conditional model using a VAR

The results in the previous section suggest that longer the horizon to measure consumption growth, the lower the estimated risk aversion γ is. Due to the data limitation, we need to add more structure to the data generating process to calculate shocks to consumption growth longer than 36 months.

Thus, in this section, we estimate the conditional model in (10), which requires the estimates for conditional expectation for long-run consumption growth, $E_t \sum_{s=0}^{\infty} \delta^s (c_{t+1+s} - c_{t+s})$. To this end, we choose a vector of state variables, and estimate the VAR in (2) and

(3).

First, we select a set of state variables that predict consumption growth. Ludvigson and Ng (2007) and Roussanov (2014) use the principal components of macro variables, and we follow their approach in selecting state variables. To this end, we use 44 macro variables listed in Table A.3, and extract the first ten principal components, $F_1, \ldots, F_{10}$. Furthermore, following Wachter (2002) and Duffee (2005), we augment these factors by the surplus ratio defined as the exponential weighted average of current and past m-month consumption growth $S_m = \frac{1-\psi}{1-\psi^m} \sum_{j=0}^{m-1} \psi^j \Delta c_{t-j}$ with $\psi = 0.96$. Because consumption growth is persistent, we expect that the surplus ratio is a good predictor of future consumption growth. We use the first ten PCA factors together with surplus ratios with $m = 3, 6, 9, 12, 24, 36$ with the maximum VAR lags of three as candidate sets of state vector variables.

Based on these candidate sets totaling 196,605, we find a subset which minimizes the Akaike Information Criterion (AIC). Table A.2 reports the values of AIC with a different combination of factors and lags. In the end, we find that the combination of F_3, F_5, F_9, S_9, S_{24}, and S_{36} with two lags minimizes the AIC. The number of state variables (total of 18) is comparable to Malloy, Moskowitz, and Vissing-Jørgensen (2009) who use 19 variables. Table A.3 reports how 44 macro variables load on the principal components that we select.

Table A.4 presents the estimated coefficients in (2) and (3). To save space, we only report coefficients for the first lag. We find that the set of state variables we choose indeed predicts consumption growth well. The first three lags of the three principal components and the 24-months surplus ratio are significant predictors of consumption growth next month with adjusted R-squared of 0.175. To predict future consumption growth, Duffee (2005) uses three lags of consumption growth at the monthly frequency, which generates adjusted R-squared of 0.0825 in our sample period. Therefore, the selected set of state variables has a much stronger predictive power than past consumption.

With this VAR estimate, we calculate shocks to the long-run expectation,

$$(E_{t+1} - E_t) \sum_{s=0}^{\infty} \delta^s (c_{t+1+s} - c_{t+s}) = \epsilon_{c,t+1} + \delta U_c (I - \delta G)^{-1} \epsilon_{x,t+1}, \tag{19}$$

where $\epsilon_{c,t+1} = \eta_0 w_{t+1}$ and $\epsilon_{x,t+1} = H w_{t+1}$. We use regression residuals of (2) and (3) for

$\epsilon_{c,t+1}$ and $\epsilon_{x,t+1}$. Table A.5 presents the summary statistics of shocks to the expectation for long-run consumption growth estimated using the VAR. We find that the standard deviation of VAR-based shocks to long-run consumption is 1.69% per month, which is slightly lower than the standard deviation of unconditional 24-month consumption growth (2.04% per month).

Armed with the estimated shocks to expectation for the long-run consumption growth in (19), we estimate the conditional model in (10) using GMM. Panel A of Table 5 reports the estimates. Using all 43 portfolios as test assets, we find that the estimated risk-aversion parameter γ is 21, which is lower than the estimate for the unconditional model of 42. The cross-sectional R-squared is high at 0.75. This superior performance of the VAR-based approach to the simple unconditional model highlights the importance of measuring the factor using consumption growth over a long horizon. We emphasize that we do not specify VARs based on how shocks to state variables covary with bond returns. Instead, the state variables are selected based only on how well they predict consumption growth. Because the selected state variables predict consumption well, they provide a better measure of long-run consumption risk, which ultimately leads to more reasonable (i.e. lower) estimates for the risk aversion parameter and better cross-sectional R-squared.

The analysis of seven subsamples also yields results similar to our main results in Table 4. These results are encouraging as we find that both conditional and unconditional models lead to consistent results supporting the performance of the long-run risk model in pricing corporate bonds.

The risk-aversion coefficient γ is intuitive and easy to compare with the literature that calibrates the long-run risk model. However, we cannot compare them with factor risk premiums associated with reduced-form factor models such as Bai, Bali, and Wen (2019). To estimate the price of the long-run risk, we employ standard two-pass regressions. In the first-stage time-series regression, we regress monthly excess returns $r_{i,t+1} - r_{f,t}$ over t to $t+1$ on the long-run consumption risk factor $(E_{t+1} - E_t) \sum_{s=0}^{\infty} \delta^s (c_{t+1+s} - c_{t+s})$,

$$r_{i,t+1} - r_{f,t} = a_i + \beta_i \left((E_{t+1} - E_t) \sum_{s=0}^{\infty} \delta^s (c_{t+1+s} - c_{t+s}) \right) + u_{p,t+1}. \tag{20}$$

In the second-stage cross-sectional regression, average excess returns $E[r_{i,t+1}-r_{f,t}]+\frac{\sigma^2(r_{i,t+1})}{2}-\frac{\sigma^2(r_{f,t})}{2}$ are regressed on estimated betas $\hat{\beta}_i$ cross-sectionally,

$$E[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} = \lambda_0 + \lambda_1 \hat{\beta}_i + \alpha_i. \tag{21}$$

As in the GMM estimates above, we compute standard errors by bootstrapping months with 5,000 replications, which corrects for cross-sectional correlation in error terms as well as the first-stage estimation errors since the re-sampled data is used for both the first- and second- stage estimation. The estimated price of risk $\hat{\lambda}_1$ measures the risk premium for an asset that has $\beta = 1$.

Panel B of Table 5 presents the price of risk based on the two-pass regressions in (20) and (21) using shocks to long-run consumption growth as a risk factor. The estimate risk premium using all 43 portfolios is 0.56% per month which is comparable to the risk premiums on the corporate bond market portfolio of 0.39% reported in Bai, Bali, and Wen (2019). The estimated intercept $\hat{\lambda}_0$ is 0.06%, which is economically small and statistically indistinguishable from zero, and thus the risk-free assets are also correctly priced. The cross-sectional R-squared is 0.78 with the 95-percent confidence interval ranging from 0.42 to 0.83, suggesting a good fit of the model.

The estimates for λ_1 for each subsample in Panel B of Table 5 ranges from 0.28% to 1.04%, and the 95% confidence interval for all of these estimates contain the full sample estimates of 0.56%. These results suggest that the long-run risk is a priced factor in the cross-section of corporate bonds, and the estimated risk premiums are consistent across the seven sets of test assets that we use.

Finally, we estimate the same two-pass regressions using unconditional 24-months consumption growth as a risk factor. The estimated price of risk and cross-sectional R-squared is reported in Table 6. We find that the estimated price of risk using all 43 portfolios is 1.73%, higher than the VAR-based results of 0.56%. The difference comes from the difference in estimated γ as well as the volatility of long-run consumption shocks. VAR estimates lead to less than half a risk aversion coefficient than the unconditional estimates, leading to more sensible estimates for the price of risk.

5 Extension

In this section, we extend our main results using several extensions and study whether the main results hold under alternative frameworks.

5.1 Different return horizon

In the main results above, we use one-month log returns on corporate bonds to estimate the quantity of long-run risk. In this section, we study whether these results hold with different return horizons to estimate the model. Lettau, Ludvigson, and Ma (2019) test an asset pricing model involving a macro economic factor, and show that due to the transitory measurement errors in their factor, using longer-horizon returns substantially improves the measurement of betas and the empirical performance of their model.

Based on these observations, we repeat the GMM-based test of the long-run risk model in (13) using 3-, 12- and 24-month returns. Table 7 reports the estimated risk aversion coefficient γ together with diagnostic statistics. Panel A of Table 7 presents the case in which we use three-month returns with different horizon for consumption ($S = 1, \ldots, 24$). Using a three-month return generates a similar value of γ to the case of one-month returns in Table 3. When $S = 1$, an estimated γ is as large as 202, suggesting that the consumption-based model with a short-term shock would require an implausible degree of risk aversion to price corporate bonds. However, as S increases, estimated γ decreases, and with $S = 12$ (which corresponds to the horizon of 36 months), the estimated γ is 45, similar to the results in Table 3.

Panels B and C of Table 7 report the estimated γ when we use one- or two-year returns. We find that, unlike Lettau, Ludvigson, and Ma (2019), using longer-horizon returns does not necessarily generate a better fit for the long-run risk model. The cross-sectional R-squared is generally high, ranging from 0.59 to 0.69 depending on the choice of S. Estimated risk-aversion coefficients are not very precise, and are mostly statistically indistinguishable from zero. These results suggest that the 44-year time span of our sample is still not long enough to estimate betas using long-horizon returns precisely.

5.2 Departure from the lognormality assumption

In deriving the Euler equation for log excess returns in (8), we assume that consumption growth and asset returns are jointly lognormally distributed. While this is a standard assumption in the literature, this assumption may not be suitable for our sample of corporate bonds. Corporate bond returns may not be lognormally distributed because in the Merton (1974) model, corporate bonds are viewed as a derivative on the underlying firm's asset, and the payoff to bonds is a nonlinear function of the asset. This feature of corporate bonds may lead to the skewed distribution of bond returns, invalidating the Euler equation derived in (8).

Harvey and Siddique (2000) present an empirical framework to test an asset pricing model accounting for skewness in asset returns. To account for the dependence in higher order moments between factors and asset returns, Harvey and Siddique (2000) express expected returns as a function of covariance and coskewness between factors and asset returns. We follow their approach, and expand the Euler equation as up to the third-order:

$$1 = E[S_{t+1}R_{i,t+1}], \tag{22}$$

$$\approx \bar{G}\left(1 + E[r_{i,t+1}] + \frac{1}{2}E[r_{i,t+1}^2] + (1-\gamma)E[\varepsilon_{c,t\to t+S}r_{i,t+1}] + \frac{1}{2}(1-\gamma)^2E[\varepsilon_{c,t\to t+S}^2 r_{i,t+1}] + \frac{1}{2}(1-\gamma)E[\varepsilon_{c,t\to t+S}r_{i,t+1}^2] + Const\right). \tag{23}$$

where $\bar{G} = e^{\log\delta - 0.5(1-\gamma)^2\eta(\delta)^2 + (1-\gamma)\mu_{\sum_{s=0}^{\infty}\delta^s\Delta c_{t+1+s}}}$. Eq (23) shows that the risk premiums depend on covariance term as well as coskewness.[13] Thus, we estimate the GMM using the moment conditions:

$$0 = E\left[\begin{array}{c}\left(\begin{array}{l} r_{i,t+1} - r_{f,t} + \frac{E(r_{i,t+1}^2)}{2} - \frac{E(r_{f,t}^2)}{2} - \zeta - (\gamma-1)\varepsilon_{c,t\to t+S}\left(r_{i,t+1} - r_{f,t}\right) \\ +\frac{1}{2}(1-\gamma)^2\varepsilon_{c,t\to t+S}^2\left(r_{i,t+1} - r_{f,t}\right) - \frac{1}{2}(\gamma-1)\varepsilon_{c,t\to t+S}\left(r_{i,t+1}^2 - r_{f,t}^2\right)\end{array}\right) \\ \varepsilon_{c,t\to t+S}\end{array}\right]. \tag{24}$$

Unlike Harvey and Siddique (2000), the regression specification in (24) restricts the

[13] The constant term in (23) is $E[(1-\gamma)\varepsilon_{c,t\to t+S}] + \frac{1}{2}E[(1-\gamma)^2\varepsilon_{c,t\to t+S}^2] + \frac{1}{6}E[(1-\gamma)^3\varepsilon_{c,t\to t+S}^3] + \frac{1}{6}E[r_{i,t+1}^3]$. Since the last term is small, we assume $E[r_{i,t+1}^3] = E[r_{f,t}^3]$ in deriving (24).

number of parameters to be the same as the main analysis, since the loadings on the covariance and coskewness both depend on γ.

Table 8 presents the estimated slope coefficients in (24) and the fit of the model using 43 bond portfolios as test assets. We find that the estimated γ is 34 and the cross-sectional R-squared is 0.65, which is slightly lower than the main results. Overall, we do not find strong evidence for the improvement in the performance of the model as we account for nonlinearity in bond returns.

5.3 Illiquidity of corporate bonds

Bai, Bali, and Wen (2019) show that illiquidity measures predict cross-section of corporate bond returns. To examine whether consumption-based model explains illiquidity premium, we sort corporate bonds into quintiles based on the Roll measure (square root of negative autocovariance of daily log price changes calculated in each month), age (time elapsed since issuance), issue amount of bonds as well as betas with respect to the noise measure of Treasury yield curve proposed by Hu, Pan, and Wang (2013). The Roll measure is available only after July 2002 when TRACE data starts.

Table 9 reports the performance of the long-run risk model using 20 illiquidity-sorted portfolios. As expected, the fit of the model is poor with low R-squared and insignificant estimates for the risk aversion coefficient. Therefore, the long-run risk model is not a panacea; it explains the cross-section of bond returns likely to be associated with default risk and macroeconomic uncertainty, but it does not explain illiquidity premiums. Consistent with our findings, Goldberg and Nozawa (2020) show that the dealer's inventory capacity is a key driver of illiquidity premium in corporate bonds, suggesting that intermediary capital provides additional information about asset prices orthogonal to household consumption risk.

5.4 Test on individual corporate bonds

The main results in Table 3 are based on portfolios of corporate bonds. Though forming portfolio enables us to estimate risks and risk premiums precisely, we potentially lose information on the variation in average returns unrelated to the sorting variables. To overcome this potential issue, we use individual corporate bonds as test assets, and repeat the two-pass regression exercise in Section 4. To make the results comparable to the main results based on portfolios, we use both covariance in (11) and betas in (20) as the right-hand side variables.

Specifically, for each individual bonds, we estimate the quantity of risk (covariance or beta) using one-month excess returns $r_{i,t+1} - r_{f,t}$ and the long-run consumption risk factor $\sum_{s=0}^{23} \delta^s (c_{t+1+s} - c_{t+s})$ on the 36-month rolling window. For each month, individual bonds are sorted into hundred portfolios based on the estimated quantity of risk over the past 36 months. Next, we compute the value-weighted portfolio returns over the next month. Using those portfolio returns, we estimate the unconditional quantity of risk for each portfolio, and assign the estimated quantity of risk to each bond in the group. Even though the quantity of risk for portfolios is constant, the quantity of risk for individual bonds varies over time as individual bonds belong to different portfolio groups over time. Finally, average one month ahead excess returns $E_T[r_{i,t+2} - r_{f,t+1}] + \frac{\sigma_T^2(r_{i,t+2})}{2} - \frac{\sigma_T^2(r_{f,t})}{2}$ are regressed on the average of assigned quantity of risk cross-sectionally,

$$
\begin{aligned}
&E_T[r_{i,t+2} - r_{f,t+1}] + \frac{\sigma_T^2(r_{i,t+2})}{2} - \frac{\sigma_T^2(r_{f,t+1})}{2} \\
&= \zeta + (\gamma - 1) E_T \left[\hat{cov} \left(r_{i,t+1} - r_{f,t}, \sum_{s=0}^{23} \delta^s (c_{t+1+s} - c_{t+s}) \right) \right] + \alpha_i, \qquad (25)
\end{aligned}
$$

$$
E_T[r_{i,t+2} - r^f_{t+1}] + \frac{\sigma_T^2(r_{i,t+2})}{2} - \frac{\sigma_T^2(r_{f,t+1})}{2} = \lambda_0 + \lambda_1 E_T[\hat{\beta}_{i,t+1}] + \alpha_i. \qquad (26)
$$

Table 10 presents the estimated parameters as well as the fit of the model. We find that the estimated risk-aversion parameter γ is 57.48, similar to the main results in Table 3. As expected, using returns at the individual bond level makes it difficult to measure expected returns precisely. As a result, we cannot statistically distinguish estimated γ from zero, and the cross-sectional R-squared is 0.02. When we use beta as a right-hand side variable, the estimated price of risk is 2.47% per month, which is roughly comparable with the portfolio-based estimates of 1.73%. Overall, the results using individual bonds are less powerful than the portfolio-based results, but the point estimates for the risk-aversion coefficient and the price of risk are consistent with the portfolio-based results.

6 Conclusion

In this article, we examine whether a consumption-based model with long-run risk can explain the cross-section of corporate bond returns or not. Consistent with the literature on equity risk premiums, we find that the long-run risk model with a modest level of risk-aversion explains the cross-section of corporate returns. Specifically, the model explains the variation in risk premiums associated with credit spreads, maturity, credit rating, downside risk, and the intermediary factor betas. This finding is consistent with the literature which explains credit spreads at the aggregate level using long-run risk models (e.g., Bhamra, Kuehn, and Strebulaev, 2010a,b; Chen, 2010; Elkamhi, Jo, and Salerno, 2020). However, in this paper, we directly estimate the quantity and price of risk using bond return data, avoiding the issue of calibrating the model to match historical default frequency.

Our results also point to the re-interpretation of the well-known class of factor models based on shocks to financial intermediary's capital (e.g. Adrian, Etula, and Muir (2014), He, Kelly, and Manela (2017)). However, our findings are not mutually exclusive with the financial intermediary-based explanation of risk premiums. It is possible to argue that depleted intermediary's capital causes households' expectations for the long-run consumption growth to fall, or vice versa. The fact that the long-run risk model generates a pattern in risk exposure that matches the intermediary-based model does not tell which shock causes the other. To tell whether consumption or intermediary capital is the fundamental source of shocks that are priced in the cross-section of corporate bonds, we need to go beyond the reduced-form analysis presented in this article.

Table 1. **Descriptive statistics**

Panel A reports the number of asset-month observations, mean, standard deviation, and percentiles of bond monthly returns. Assets are 10 credit spread-sorted portfolios, 5 downside risk-sorted portfolios, 5 maturity-sorted portfolios, 5 credit rating-sorted portfolios, 5 intermediary factor (He, Kelly, and Manela, 2017) beta-sorted portfolios, 5 idiosyncratic volatility-sorted portfolios, and 8 Treasury bond portfolios. Panel B reports the descriptive statistics of the long-run consumption risk measure and its short-run and long-run component where $\delta = 0.95^{1/12}$ and c_t is the log consumption. The long-run consumption risk is measured as discounted consumption growth over 24 months horizons. Time period spans from February 1973 to June 2017.

				Percentiles (%)						
	N	Mean (%)	SD (%)	1st	5th	25th	50th	75th	95th	99th
Panel A: Test assets return										
Credit spread portfolios	5,220	0.70	2.19	-5.22	-2.48	-0.31	0.73	1.66	3.89	7.10
Downside portfolios	2,545	0.72	2.00	-4.96	-2.17	-0.12	0.70	1.54	3.71	7.01
Maturity portfolios	2,665	0.71	2.08	-4.99	-2.51	-0.23	0.70	1.65	3.73	7.30
Rating portfolios	2,649	0.72	2.24	-5.30	-2.68	-0.32	0.76	1.74	3.90	7.08
Intermediary portfolios	2,605	0.67	2.06	-5.25	-2.46	-0.25	0.68	1.55	3.58	7.20
Idiosyncratic volatility portfolios	2,545	0.72	2.00	-4.98	-2.29	-0.15	0.68	1.55	3.71	7.28
Government bonds	4,264	0.58	2.09	-5.09	-2.62	-0.11	0.45	1.29	3.86	7.59
Individual bonds	2,390,407	0.83	5.98	-8.32	-3.59	-0.33	0.71	1.87	5.28	11.09
Panel B: Long-run consumption risk										
$\sum_{s=0}^{23} \delta^s (c_{t+1+s} - c_{t+s})$	533	3.89	2.04	-1.20	0.22	2.32	4.08	5.35	6.96	7.42
$c_{t+1} - c_t$	533	0.17	0.32	-0.70	-0.33	-0.01	0.16	0.35	0.69	1.00
$\sum_{s=0}^{23} \delta^s (c_{t+1+s} - c_{t+s}) - (c_{t+1} - c_t)$	533	3.72	1.97	-1.31	0.19	2.20	3.88	5.16	6.66	7.10

Table 2. **Average returns and covariances**

This table reports average excess returns, $\hat{E}(r_{i,t+1} - r_{f,t}) + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2}$ and the quantity of risk for the short-run component (denoted by SR): $\hat{cov}(c_{t+1} - c_t, r_{i,t+1} - r_{f,t})$ and the long-run component (denoted by LR): $\hat{cov}(\sum_{s=1}^{24} \delta^s (c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_t^f)$ for each portfolio group where $r_{i,t+1}$ is the monthly log return of an asset i, $r_{f,t}$ is the monthly log rate of 30-day T-bill, $\delta = 0.95^{1/12}$, c_t is the log consumption. The long-run consumption risk is measured as discounted consumption growth over 24 months horizons. The covariances are computed as the unconditional sample covariances. Bootstrapped standard errors computed with 5,000 replications are reported in parentheses. Time period spans from February 1973 to June 2017.

Panel A: Credit spread portfolios

	Low 1	2	3	4	5	6	7	8	9	High 10	High - Low 10 - 1
Returns (%)	0.1866	0.2265	0.2263	0.2431	0.2737	0.3236	0.3263	0.3446	0.3330	0.6157	0.4291
	(0.0567)	(0.0538)	(0.0536)	(0.0552)	(0.0612)	(0.0654)	(0.0643)	(0.0627)	(0.0625)	(0.1008)	(0.0898)
SR (%)	2×10^{-5}	8×10^{-5}	2×10^{-4}	1×10^{-4}	2×10^{-4}	1×10^{-4}	2×10^{-4}	3×10^{-4}	5×10^{-4}	6×10^{-4}	6×10^{-4}
	(1×10^{-4})	(1×10^{-4})	(2×10^{-4})	(2×10^{-4})	(2×10^{-4})	(2×10^{-4})	(2×10^{-4})	(1×10^{-4})	(2×10^{-4})	(2×10^{-4})	(2×10^{-4})
LR (%)	0.0026	0.0032	0.0036	0.0042	0.0047	0.0054	0.0057	0.0063	0.0075	0.0087	0.0061
	(0.0013)	(0.0019)	(0.0022)	(0.0023)	(0.0024)	(0.0023)	(0.0024)	(0.0023)	(0.0021)	(0.0024)	(0.0021)

Panel B: Downside portfolios

	Low 1	2	3	4	High 5	High - Low 5 - 1
Returns (%)	0.2031	0.2672	0.3258	0.3859	0.5062	0.3031
	(0.0286)	(0.0439)	(0.0541)	(0.0628)	(0.0700)	(0.0472)
SR (%)	4×10^{-5}	1×10^{-4}	1×10^{-4}	1×10^{-4}	3×10^{-4}	3×10^{-4}
	(7×10^{-5})	(1×10^{-4})	(1×10^{-4})	(1×10^{-4})	(2×10^{-4})	(9×10^{-5})
LR (%)	0.0028	0.0044	0.0050	0.0060	0.0057	0.0030
	(0.0015)	(0.0021)	(0.0023)	(0.0022)	(0.0023)	(0.0011)

Panel C: Maturity portfolios

	Low 1	2	3	4	High 5	High - Low 5 - 1
Returns (%)	0.2733	0.2900	0.3030	0.3067	0.4144	0.1411
	(0.0332)	(0.0480)	(0.0582)	(0.0559)	(0.0678)	(0.0389)
SR (%)	1×10^{-4}	3×10^{-4}	4×10^{-4}	3×10^{-4}	4×10^{-4}	3×10^{-4}
	(7×10^{-5})	(1×10^{-4})	(2×10^{-4})	(2×10^{-4})	(2×10^{-4})	(1×10^{-4})
LR (%)	0.0039	0.0050	0.0060	0.0066	0.0072	0.0033
	(0.0011)	(0.0019)	(0.0021)	(0.0022)	(0.0021)	(0.0010)

Panel D: Rating portfolios

	Low 1	2	3	4	High 5	High - Low 5 - 1
Returns (%)	0.2312	0.2606	0.2972	0.3785	0.4908	0.2596
	(0.0557)	(0.0580)	(0.0535)	(0.0563)	(0.0620)	(0.0689)
SR (%)	2×10^{-4}	1×10^{-4}	2×10^{-4}	5×10^{-4}	9×10^{-4}	7×10^{-4}
	(2×10^{-4})	(1×10^{-4})	(2×10^{-4})	(5×10^{-4})	(9×10^{-4})	(7×10^{-4})
LR (%)	0.0045	0.0045	0.0057	0.0068	0.0086	0.0041
	(0.0020)	(0.0023)	(0.0024)	(0.0023)	(0.0019)	(0.0015)

Panel E: Intermediary beta portfolios

	Low 1	2	3	4	High 5	High - Low 5 - 1
Returns (%)	0.2598	0.2530	0.2802	0.2751	0.3560	0.0962
	(0.0454)	(0.0497)	(0.0579)	(0.0598)	(0.0752)	(0.0518)
SR (%)	1×10^{-4}	1×10^{-4}	2×10^{-4}	2×10^{-4}	3×10^{-4}	1×10^{-4}
	(1×10^{-4})	(2×10^{-4})	(2×10^{-4})	(2×10^{-4})	(2×10^{-4})	(9×10^{-5})
LR (%)	0.0047	0.0041	0.0046	0.0052	0.0065	0.0018
	(0.0014)	(0.0020)	(0.0022)	(0.0022)	(0.0020)	(8×10^{-4})

Panel F: Idiosyncratic portfolios

	Low 1	2	3	4	High 5	High - Low 5 - 1
Returns (%)	0.2259	0.2892	0.3607	0.3670	0.4407	0.2149
	(0.0318)	(0.0468)	(0.0558)	(0.0608)	(0.0631)	(0.0404)
SR (%)	5×10^{-5}	2×10^{-4}	2×10^{-4}	1×10^{-4}	3×10^{-4}	2×10^{-4}
	(6×10^{-5})	(1×10^{-4})	(2×10^{-4})	(1×10^{-4})	(1×10^{-4})	(1×10^{-4})
LR (%)	0.0029	0.0042	0.0052	0.0056	0.0063	0.0033
	(0.0014)	(0.0022)	(0.0022)	(0.0023)	(0.0020)	(0.0010)

Panel G: Treasury bond portfolios

	Short 90m	1-yr	2-yr	5-yr	7-yr	10-yr	20-yr	Long 30-yr	Long - Short 30-yr - 90m
Returns (%)	0.0372	0.0871	0.1175	0.1893	0.2380	0.2352	0.3211	0.3002	0.2631
	(0.0076)	(0.0178)	(0.0236)	(0.0416)	(0.0500)	(0.0510)	(0.0767)	(0.0723)	(0.0753)
SR (%)	4×10^{-6}	2×10^{-6}	-4×10^{-5}	-2×10^{-4}	-3×10^{-4}	-2×10^{-4}	-2×10^{-4}	-7×10^{-5}	-7×10^{-5}
	(6×10^{-6})	(3×10^{-5})	(6×10^{-5})	(9×10^{-5})	(1×10^{-4})	(1×10^{-4})	(2×10^{-4})	(3×10^{-4})	(3×10^{-4})
LR (%)	2×10^{-4}	0.0011	0.0014	0.0018	0.0016	0.0020	0.0033	0.0027	0.0025
	(8×10^{-5})	(6×10^{-4})	(9×10^{-4})	(0.0015)	(0.0018)	(0.0018)	(0.0023)	(0.0025)	(0.0024)

Table 3. **Cross-sectional regression using GMM using all portfolios**

The following regression is run: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} = \zeta + (\gamma - 1)c\hat{o}v(\sum_{s=0}^{S-1} \delta^s(c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) + e_i$ where $r_{i,t+1}$ is the monthly log return of an asset i, $r_{f,t}$ is the log monthly rate of 30-day T-bill, $\delta = 0.95^{1/12}$, c_t is the log consumption. The long-run consumption risk is measured as discounted consumption growth over horizons of $S = 1$, 3, 6, 9, 12, 24, 36 months. The quantity of risk is jointly estimated with parameters ζ, η, and γ using GMM. Test assets are 43 portfolios including 10 credit spread-sorted portfolios, 5 downside risk-sorted portfolios, 5 maturity-sorted portfolios, 5 credit rating-sorted portfolios, 5 intermediary factor (He, Kelly, and Manela, 2017) beta-sorted portfolios, 5 idiosyncratic volatility-sorted portfolios, and 8 Treasury bond portfolios Reported are the intercepts ζ, η and implied risk aversion coefficients γ with 95% confidence intervals for parameters, based on bootstrapping with 5,000 replications in square brackets. The cross-sectional $\bar{R}^2$ is defined as $1 - var_c(E(R_i^e) - \widehat{R^e}_i)/var_c(E(R_i^e))$ where i is a test asset and $\widehat{R^e}_i$ is the predicted average excess return of portfolio i. 95% confidence intervals for $\bar{R}^2$ are reported in square brackets. The pricing error is measured by $\frac{RMSE}{RMSR}$ where $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E(R_i^e) - \widehat{R^e}_i)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N} E(R_i^e)^2}$. Time period spans from February 1973 to June 2017. Unconditional pricing errors ζ and η are multiplied by 100 for ease of exposition.

S (months) =	1	3	6	9	12	24	36
Panel A: Regressions: $E[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} = \zeta + (\gamma - 1)c\hat{o}v(\sum_{s=0}^{S-1} \delta^s(c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) + e_i$							
ζ	0.22	0.13	0.09	0.09	0.09	0.09	0.06
	[0.09 0.37]	[0.02 0.31]	[0.02 0.31]	[0.01 0.33]	[-0.01 0.33]	[-0.02 0.32]	[-0.01 0.30]
γ	335.31	196.10	94.74	66.56	61.04	42.56	44.82
	[150.91 507.59]	[87.10 305.53]	[36.35 176.02]	[24.46 117.63]	[24.75 98.09]	[18.23 70.11]	[16.24 77.61]
$\bar{R}^2$	0.53	0.77	0.66	0.66	0.73	0.74	0.75
	[0.12 0.71]	[0.34 0.81]	[0.24 0.72]	[0.20 0.71]	[0.25 0.77]	[0.27 0.78]	[0.25 0.80]
$\frac{RMSE}{RMSR}$	0.23	0.16	0.19	0.19	0.17	0.17	0.16
Number of assets	43	43	43	43	43	43	43
Number of asset-month	22,493	22,493	22,493	22,493	22,493	22,493	22,106
Panel B: Reverse regressions: $c\hat{o}v(\sum_{s=0}^{S-1} \delta^s(c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) = \eta + \frac{1}{(\gamma-1)}(E[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2}) + u_i$							
η	-2$\times 10^{-4}$	-3$\times 10^{-4}$	9$\times 10^{-5}$	2$\times 10^{-4}$	-2$\times 10^{-4}$	-4$\times 10^{-4}$	3 $\times 10^{-4}$
	[-4$\times 10^{-4}$ -4$\times 10^{-6}$]	[-7$\times 10^{-4}$ 5$\times 10^{-4}$]	[-9$\times 10^{-4}$ 0.0021]	[-0.0015 0.0036]	[-0.0019 0.0032]	[-0.0028 0.0046]	[-0.0020 0.0053]
γ	688.49	258.61	144.07	100.13	83.14	57.10	59.33
	[368.93 2,859]	[165.91 575.90]	[90.04 405.95]	[63.61 313.32]	[53.80 215.48]	[37.31 150.05]	[35.32 166.97]
$\bar{R}^2$	0.49	0.76	0.66	0.66	0.73	0.74	0.75
	[0.06 0.69]	[0.32 0.80]	[0.23 0.72]	[0.20 0.71]	[0.25 0.77]	[0.27 0.78]	[0.25 0.80]
$\frac{RMSE}{RMSR}$	0.55	0.23	0.23	0.22	0.21	0.21	0.18
Number of assets	43	43	43	43	43	43	43
Number of asset-month	22,493	22,493	22,493	22,493	22,493	22,493	22,106

Table 4. **Cross-sectional regression using GMM for each portfolio group**

The following regression is run: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} = \zeta + (\gamma - 1)\hat{cov}(\sum_{s=0}^{S-1} \delta^s(c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) + e_i$ where $r_{i,t+1}$ is the monthly log return of an asset i, $r_{f,t}$ is the monthly log rate of 30-day T-bill, $\delta = 0.95^{1/12}$, c_t is the log consumption. The long-run consumption risk is measured as discounted consumption growth over 24 months horizons. The quantity of risk is jointly estimated with parameters ζ and γ using GMM. Test assets are 10 credit spread-sorted portfolios, 5 downside risk-sorted portfolios, 5 maturity-sorted portfolios, 5 credit rating-sorted portfolios, 5 intermediary factor (He, Kelly, and Manela, 2017) beta-sorted portfolios, 5 idiosyncratic volatility-sorted portfolios, and 8 Treasury bond portfolios. Reported are the intercepts ζ and implied risk aversion coefficients γ with 95% confidence intervals for parameters, based on bootstrapping with 5,000 replications in square brackets. The cross-sectional $\bar{R}^2$ is defined as $1 - var_c(E(R_i^e) - \widehat{R^e}_i)/var_c(E(R_i^e))$ where i is a test asset and $\widehat{R^e}_i$ is the predicted average excess return of portfolio i. 95% confidence intervals for $\bar{R}^2$ are reported in square brackets. The pricing error is measured by $\frac{RMSE}{RMSR}$ where $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E(R_i^e) - \widehat{R^e}_i)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N} E(R_i^e)^2}$. Time period spans from February 1973 to June 2017. Unconditional pricing errors ζ are multiplied by 100 for ease of exposition.

Assets	Credit Spread portfolios	Downside portfolios	Maturity portfolios	Rating portfolios	Intermediary portfolios	IdioVol portfolios	Treasury portfolios
ζ	0.03	-0.04	0.13	0.01	0.08	0.04	0.02
	[-0.24 0.31]	[-0.15 0.26]	[0.05 0.23]	[-0.67 0.34]	[0.003 0.35]	[-0.06 0.33]	[-0.01 0.24]
γ	52.62	77.69	32.55	51.70	41.16	60.24	103.03
	[25.02 90.33]	[30.80 176.01]	[5.48 95.24]	[18.42 119.74]	[-9.21 66.25]	[20.37 116.92]	[-196.83 168.92]
$\bar{R}^2$	0.82	0.79	0.62	0.99	0.90	0.99	0.84
	[0.34 0.92]	[0.40 0.94]	[0.08 0.90]	[0.49 0.99]	[0.01 0.95]	[0.34 0.99]	[0.02 0.96]
$\frac{RMSE}{RMSR}$	0.15	0.13	0.10	0.03	0.04	0.03	0.18
Number of assets	10	5	5	5	5	5	8
Number of asset-month	5,220	2,545	2,665	2,649	2,605	2,545	4,264

Table 5. **Tests using the VAR**

This table presents the results using the VAR. In this table the long-run consumption risk factor is measured as $(\hat{E}_{t+1} - \hat{E}_t)\sum_{s=0}^{\infty}\delta^s(c_{t+1+s} - c_{t+s})$, which is based on the VAR. In Panel A, the GMM test is run where the quantity of risk is jointly estimated with parameters of average pricing errors α and risk aversion γ. In Panel B, two-pass regression is run where average excess returns are regressed on estimated betas cross-sectionally. Test assets are 10 credit spread-sorted portfolios, 5 downside risk-sorted portfolios, 5 maturity-sorted portfolios, 5 credit rating-sorted portfolios, 5 intermediary factor (He, Kelly, and Manela, 2017) beta-sorted portfolios, 5 idiosyncratic volatility-sorted portfolios, and 8 Treasury bond portfolios. 95% confidence intervals for parameters, based on bootstrapping with 5,000 replications, are reported in square brackets. The cross-sectional $\bar{R}^2$ is defined as $1 - var_c(E(R_i^e) - \widehat{R^e}_i)/var_c(E(R_i^e))$ where i is a test asset and $\widehat{R^e}_i$ is the predicted average excess return of portfolio i. 95% confidence intervals for $\bar{R}^2$ are reported in square brackets. The pricing error is measured by $\frac{RMSE}{RMSR}$ where $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E(R_i^e) - \widehat{R^e}_i)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N}E(R_i^e)^2}$. Time period spans from February 1973 to June 2017. Unconditional pricing errors ζ and λ_0 and prices of risk λ_1 in Panel B are multiplied by 100 for ease of exposition.

Assets	Credit Spread portfolios	Downside portfolios	Maturity portfolios	Rating portfolios	Intermediary portfolios	IdioVol portfolios	Treasury portfolios	All portfolios
Panel A: Cross-sectional regression using GMM								
ζ	-0.07	0.01	0.18	-0.20	0.01	0.11	0.06	0.06
	[-0.24 0.12]	[-0.05 0.11]	[0.12 0.24]	[-0.61 0.21]	[-0.08 0.31]	[0.03 0.21]	[0.03 0.10]	[-0.003 0.17]
γ	30.06	28.21	10.82	37.73	22.76	20.48	25.82	20.80
	[17.28 55.49]	[17.11 48.42]	[2.94 21.67]	[16.21 71.85]	[-3.59 34.48]	[11.40 34.77]	[7.50 68.38]	[11.36 34.56]
$\bar{R}^2$	0.77	0.96	0.64	0.99	0.93	0.96	0.98	0.78
	[0.39 0.93]	[0.74 1.00]	[0.06 0.92]	[0.43 1.00]	[0.00 0.97]	[0.65 0.98]	[0.84 0.99]	[0.42 0.83]
$\frac{RMSE}{RMSR}$	0.17	0.06	0.09	0.03	0.03	0.04	0.07	0.17
Number of assets	10	5	5	5	5	5	8	43
Number of asset-month	5,220	2,545	2,665	2,649	2,605	2,545	4,264	22,493
Panel B: Two-pass regression								
λ_0	-0.07	0.02	0.18	-0.20	-0.01	0.11	0.06	0.06
	[-0.24 0.11]	[-0.05 0.11]	[0.12 0.24]	[-0.58 0.21]	[-0.08 0.31]	[0.03 0.21]	[0.03 0.10]	[-0.005 0.17]
λ_1	0.82	0.75	0.28	1.04	0.62	0.54	0.71	0.56
	[0.45 1.46]	[0.48 1.21]	[0.06 0.53]	[0.40 1.91]	[-0.14 0.88]	[0.29 0.86]	[0.20 1.67]	[0.32 0.89]
$\bar{R}^2$	0.77	0.96	0.64	0.99	0.93	0.96	0.98	0.79
	[0.41 0.92]	[0.73 1.00]	[0.06 0.92]	[0.44 1.00]	[0.01 0.98]	[0.64 0.98]	[0.84 0.99]	[0.43 0.84]
$\frac{RMSE}{RMSR}$	0.17	0.06	0.09	0.03	0.03	0.04	0.07	0.15
Number of assets	10	5	5	5	5	5	8	43
Number of asset-month	5,220	2,545	2,665	2,649	2,605	2,545	4,264	22,493

Table 6. **Two-pass regression**

This table reports two-pass regression results. In the first-stage time-series regression, excess returns $r_{i,t+1} - r_{f,t}$ are regressed on the long-run consumption risk factor $\sum_{s=0}^{23} \delta^s (c_{t+1+s} - c_{t+s})$ at month $t+1$ where $r_{i,t+1}$ is the monthly log return of an asset i, $r_{f,t}$ is the monthly log rate of 30-day T-bill, $\delta = 0.95^{1/12}$, and c_t is the log consumption. The long-run consumption risk is measured as discounted consumption growth over 24 months horizons. In the second-stage cross-sectional regression, average one month ahead excess returns $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2}$ are regressed on estimated betas $\hat{\beta}_i$ cross-sectionally. Test assets are 43 portfolios including 10 credit spread-sorted portfolios, 5 downside risk-sorted portfolios, 5 maturity-sorted portfolios, 5 credit rating-sorted portfolios, 5 intermediary factor (He, Kelly, and Manela, 2017) beta-sorted portfolios, 5 idiosyncratic volatility-sorted portfolios, and 8 Treasury bond portfolios. Reported are the intercepts α and the price of risk λ with 95% confidence intervals for parameters, based on bootstrapping with 5,000 replications in square brackets. The cross-sectional $\bar{R}^2$ is defined as $1 - var_c(E(R_i^e) - \widehat{R^e}_i)/var_c(E(R_i^e))$ where i is a test asset and $\widehat{R^e}_i$ is the predicted average excess return of portfolio i. 95% confidence intervals for $\bar{R}^2$ are reported in square brackets. The pricing error is measured by $\frac{RMSE}{RMSR}$ where $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^N (E(R_i^e) - \widehat{R^e}_i)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^N E(R_i^e)^2}$. Time period spans from February 1973 to June 2017. Coefficients are multiplied by 100 for ease of exposition.

Assets	Credit Spread portfolios	Downside portfolios	Maturity portfolios	Rating portfolios	Intermediary portfolios	IdioVol portfolios	Treasury portfolios	All portfolios
λ_0	0.03	-0.04	0.13	0.01	0.08	0.04	0.02	0.09
	[-0.24 0.31]	[-0.15 0.26]	[0.06 0.23]	[-0.70 0.34]	[0.01 0.34]	[-0.06 0.33]	[-0.001 0.24]	[-0.01 0.32]
λ_1	2.10	3.17	1.31	2.10	1.64	2.45	4.25	1.73
	[0.93 3.00]	[1.16 6.58]	[0.18 3.53]	[0.72 4.10]	[-0.30 2.55]	[0.82 4.17]	[-7.62 6.22]	[0.69 2.50]
$\bar{R}^2$	0.82	0.79	0.62	0.99	0.90	0.99	0.84	0.73
	[0.33 0.92]	[0.40 0.94]	[0.07 0.90]	[0.47 0.99]	[0.01 0.95]	[0.36 1.00]	[0.01 0.96]	[0.25 0.79]
$\frac{RMSE}{RMSR}$	0.15	0.13	0.10	0.03	0.04	0.03	0.18	0.17
Number of assets	10	5	5	5	5	5	8	43
Number of asset-month	5,220	2,545	2,665	2,649	2,605	2,545	4,264	22,493

Table 7. **Extension 1: Horizon**

With different frequencies, the following cross-sectional regression is run, $\hat{E}[r_{i,t+1-m\to t+1} - r_{f,t-m\to t}] + \frac{\sigma^2(r_{i,t+1-m\to t+1})}{2} - \frac{\sigma^2(r_{f,t-m\to t})}{2} = \zeta + (\gamma-1)\hat{cov}(\sum_{s=0}^{S-1}\delta^s(c_{t+m\cdot s+1} - c_{t+m\cdot(s-1)+1}), r_{i,t+1-m\to t+1} - r_{f,t-m\to t}) + e_i$ where $r_{i,t+1-m\to t+1} = \sum_{\tau=0}^{m-1} r^i_{i,t+1-\tau}$ is the m-month cumulative log return of an asset i at month $t+1$, $r_{f,t-m\to t} = \sum_{\tau=0}^{m-1} r_{f,t-\tau}$ is the m-month cumulative log rate of 30-day T-bill at month t, $\delta = 0.95^{1/12}$, and c_t is the log consumption. The quantity of risk is jointly estimated with parameters ζ and γ using GMM. Test assets are 43 portfolios including 10 credit spread-sorted portfolios, 5 downside risk-sorted portfolios, 5 maturity-sorted portfolios, 5 credit rating-sorted portfolios, 5 intermediary factor (He, Kelly, and Manela, 2017) beta-sorted portfolios, 5 idiosyncratic volatility-sorted portfolios, and 8 Treasury bond portfolios. Reported are the intercepts ζ and implied risk aversion coefficients γ with 95% confidence intervals for parameters, based on bootstrapping with 5,000 replications in square brackets. The cross-sectional $\bar{R}^2$ is defined as $1 - var_c(E(R^e_i) - \widehat{R^e}_i)/var_c(E(R^e_i))$ where i is a test asset and $\widehat{R^e}_i$ is the predicted average excess return of portfolio i. 95% confidence intervals for $\bar{R}^2$ are reported in square brackets. The pricing error is measured by $\frac{RMSE}{RMSR}$ where $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E(R^e_i) - \widehat{R^e}_i)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N}E(R^e_i)^2}$. Time period spans from February 1973 to June 2017. Unconditional pricing errors ζ are multiplied by 100 for ease of exposition.

$S=$	1	3	6	9	12	24
Panel A: 3-month return and long-run risk factor ($m=3$)						
ζ	0.64	0.32	0.39	0.33	0.22	0.70
	[0.27 0.95]	[0.06 1.00]	[0.03 1.04]	[-0.03 1.01]	[-0.02 0.89]	[0.24 1.10]
γ	212.49	74.08	46.97	44.17	45.01	37.93
	[104.41 291.35]	[29.59 119.17]	[22.07 71.56]	[20.02 68.04]	[18.47 74.61]	[-68.22 66.21]
$\bar{R}^2$	0.63	0.64	0.67	0.70	0.71	0.12
	[0.28 0.78]	[0.24 0.71]	[0.24 0.75]	[0.28 0.78]	[0.30 0.79]	[0.00 0.64]
$\frac{RMSE}{RMSR}$	0.20	0.20	0.19	0.18	0.17	0.32
Number of assets	43	43	43	43	43	43
Number of asset-month	21,391	22,391	22,391	22,391	22,090	20,542

$S=$	1	2	3	4
Panel B: 1-year return and long-run risk factor ($m=12$)				
ζ	0.81	1.18	0.75	0.66
	[0.03 2.28]	[-0.07 3.44]	[-0.18 3.04]	[-0.005 2.69]
γ	99.31	53.92	51.83	52.26
	[-110.50 116.81]	[24.51 74.66]	[20.99 75.45]	[14.61 78.32]
$\bar{R}^2$	0.69	0.68	0.69	0.60
	[0.38 0.80]	[0.35 0.77]	[0.40 0.78]	[0.32 0.76]
$\frac{RMSE}{RMSR}$	0.18	0.18	0.18	0.20
Number of assets	43	43	43	43
Number of asset-month	21,932	21,932	21,932	21,502
Panel C: 2-year return and long-run risk factor ($m=24$)				
ζ	1.06	1.11	4.60	3.92
	[-0.14 4.07]	[0.07 4.68]	[0.43 6.05]	[0.41 5.84]
γ	63.04	45.20	-49.90	-50.52
	[-66.70 69.20]	[-56.01 59.58]	[-57.99 53.41]	[-57.69 62.28]
$\bar{R}^2$	0.68	0.59	0.61	0.68
	[0.40 0.83]	[0.33 0.77]	[0.27 0.80]	[0.35 0.84]
$\frac{RMSE}{RMSR}$	0.18	0.21	0.21	0.18
Number of assets	43	43	43	43
Number of asset-month	21,320	21,320	20,374	19,342

Table 8. **Extension 2: Skewness**

The following regression is run: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{1}{2}\hat{E}[r^2_{i,t+1}] - \frac{1}{2}\hat{E}[r^2_{f,t}] = \zeta + (\gamma - 1)\hat{E}[\epsilon_{c,t\to t+S}(r_{i,t+1} - r_{f,t+1})] - \frac{1}{2}(1-\gamma)^2\hat{E}[\epsilon^2_{c,t\to t+S}(r_{i,t+1} - r_{f,t})] + \frac{1}{2}(\gamma - 1)\hat{E}[\epsilon_{c,t\to t+S}(r^2_{i,t+1} - r^2_{f,t})] + e_i$ where $\epsilon_{c,t\to t+S} = \sum_{s=0}^{S}\delta^s(c_{t+1+s} - c_{t+s}) - \mu_{\sum_{s=0}^{S}\delta^s(c_{t+1+s}-c_{t+s})}$, $r_{i,t+1}$ is the monthly log return of an asset i, $r_{f,t}$ is the monthly log rate of 30-day T-bill, $\delta = 0.95^{1/12}$, and c_t is the log consumption. The long-run consumption risk is measured as discounted consumption growth over 24 months horizons ($S = 24$). The quantity of risk is jointly estimated with parameters ζ and γ using GMM. Test assets are 43 portfolios including 10 credit spread-sorted portfolios, 5 downside risk-sorted portfolios, 5 maturity-sorted portfolios, 5 credit rating-sorted portfolios, 5 intermediary factor (He, Kelly, and Manela, 2017) beta-sorted portfolios, 5 idiosyncratic volatility-sorted portfolios, and 8 Treasury bond portfolios. Reported are the intercepts ζ and two coefficients γ_1 and γ_2 with 95% confidence intervals for parameters, based on bootstrapping with 5,000 replications in square brackets. The cross-sectional $\bar{R}^2$ is defined as $1 - var_c(E(R^e_i) - \widehat{R^e}_i)/var_c(E(R^e_i))$ where i is a test asset and $\widehat{R^e}_i$ is the predicted average excess return of portfolio i. 95% confidence intervals for $\bar{R}^2$ are reported in square brackets. The pricing error is measured by $\frac{RMSE}{RMSR}$ where $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E(R^e_i) - \widehat{R^e}_i)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N}E(R^e_i)^2}$. Time period spans from February 1973 to June 2017. Unconditional pricing errors ζ are multiplied by 100 for ease of exposition.

ζ	0.16
	[0.02 0.38]
γ	33.60
	[14.66 45.72]
$\bar{R}^2$	0.65
	[0.16 0.71]
$\frac{RMSE}{RMSR}$	0.20
Number of assets	43
Number of asset-month	22,493

Table 9. **Test on illiquidity portfolios**

The following regression is run: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} = \zeta + (\gamma - 1)c\hat{o}v(\sum_{s=0}^{23} \delta^s(c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) + e_i$ where $r_{i,t+1}$ is the monthly log return of an asset i, $r_{f,t}$ is the monthly log rate of 30-day T-bill, $\delta = 0.95^{1/12}$, c_t is the log consumption. The long-run consumption risk is measured as discounted consumption growth over 24 months horizons. The quantity of risk is jointly estimated with parameters ζ and γ using GMM. Test assets are 5 noise factor Hu, Pan, and Wang (2013) beta-sorted portfolios, 5 age sorted portfolios, 5 issue amount sorted portfolios, and 5 Roll measure of illiquidity-sorted portfolios. Reported are the intercepts ζ and implied risk aversion coefficients γ with 95% confidence intervals for parameters, based on bootstrapping with 5,000 replications in square brackets. The cross-sectional $\bar{R}^2$ is defined as $1 - var_c(E(R_i^e) - \widehat{R^e}_i)/var_c(E(R_i^e))$ where i is a test asset and $\widehat{R^e}_i$ is the predicted average excess return of portfolio i. 95% confidence intervals for $\bar{R}^2$ are reported in square brackets. The pricing error is measured by $\frac{RMSE}{RMSR}$ where $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E(R_i^e) - \widehat{R^e}_i)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N}E(R_i^e)^2}$. Time period spans from February 1973 to June 2017. Unconditional pricing errors ζ are multiplied by 100 for ease of exposition.

ζ	0.44
	[0.18 0.52]
γ	-18.42
	[-38.57 76.60]
$\bar{R}^2$	0.27
	[0.00 0.82]
$\frac{RMSE}{RMSR}$	0.25
Number of assets	20
Number of asset-month	7,875

Table 10. **Test on individual corporate bonds**

This table reports a cross-sectional test using all available individual corporate bond. For each individual bonds, the quantity of risk (covariance or beta) is estimated by regressing excess returns $r_{i,t+1} - r_{f,t}$ on the long-run consumption risk factor $\sum_{s=0}^{23} \delta^s (c_{t+1+s} - c_{t+s})$ over the past 36-months, where $r_{i,t+1}$ is the monthly log return of an asset i, $r_{f,t}$ is the monthly log rate of 30-day T-bill, $\delta = 0.95^{1/12}$, and c_t is the log consumption. The long-run consumption risk is measured as discounted consumption growth over 24 months horizons. For each month, individuals bonds are sorted into hundred portfolios based on past 36-months quantity of risk. Next, we compute the value-weighted portfolio returns over the next month. We then estimate the unconditional quantity of risk for each portfolio, and assign the estimated quantity of risk to each bond in the group. Even though the quantity of risk for portfolios is constant, the quantity of risk for individual bonds varies over time as individual bonds belong to different portfolio groups over time. Finally, average one month ahead excess returns $E_T[r_{i,t+2} - r_{f,t+1}] + \frac{\sigma_T^2(r_{i,t+2})}{2} - \frac{\sigma_T^2(r_{f,t+1})}{2}$ are regressed on the average of assigned quantity of risk $E_T[\hat{\beta}_{i,t+1}]$ cross-sectionally. Reported are the intercepts (unconditional pricing errors) and the price of risk with 95% confidence intervals for parameters, based on bootstrapping with 5,000 replications in square brackets. The cross-sectional $\bar{R}^2$ is defined as $1 - var_c(E(R_i^e) - \widehat{R^e}_i)/var_c(E(R_i^e))$ where i is a test asset and $\widehat{R^e}_i$ is the predicted average excess return of portfolio i. 95% confidence intervals for $\bar{R}^2$ are reported in square brackets. The pricing error is measured by $\frac{RMSE}{RMSR}$ where $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E(R_i^e) - \widehat{R^e}_i)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N} E(R_i^e)^2}$. Time period spans from February 1973 to June 2017. Unconditional pricing errors and the price of risk for the beta representation are multiplied by 100 for ease of exposition.

Quantity of risk	Covariance	Beta
Unconditional pricing errors	0.05	0.05
	[-0.24 0.92]	[-0.24 0.91]
Price of risk	57.48	2.47
	[-75.31 74.76]	[-0.24 3.30]
$\bar{R}^2$	0.02	0.02
	[0.00 0.05]	[0.00 0.05]
$\frac{RMSE}{RMSR}$	0.71	0.71
Number of assets	17,845	17,845
Number of asset-month	1,837,586	1,837,586

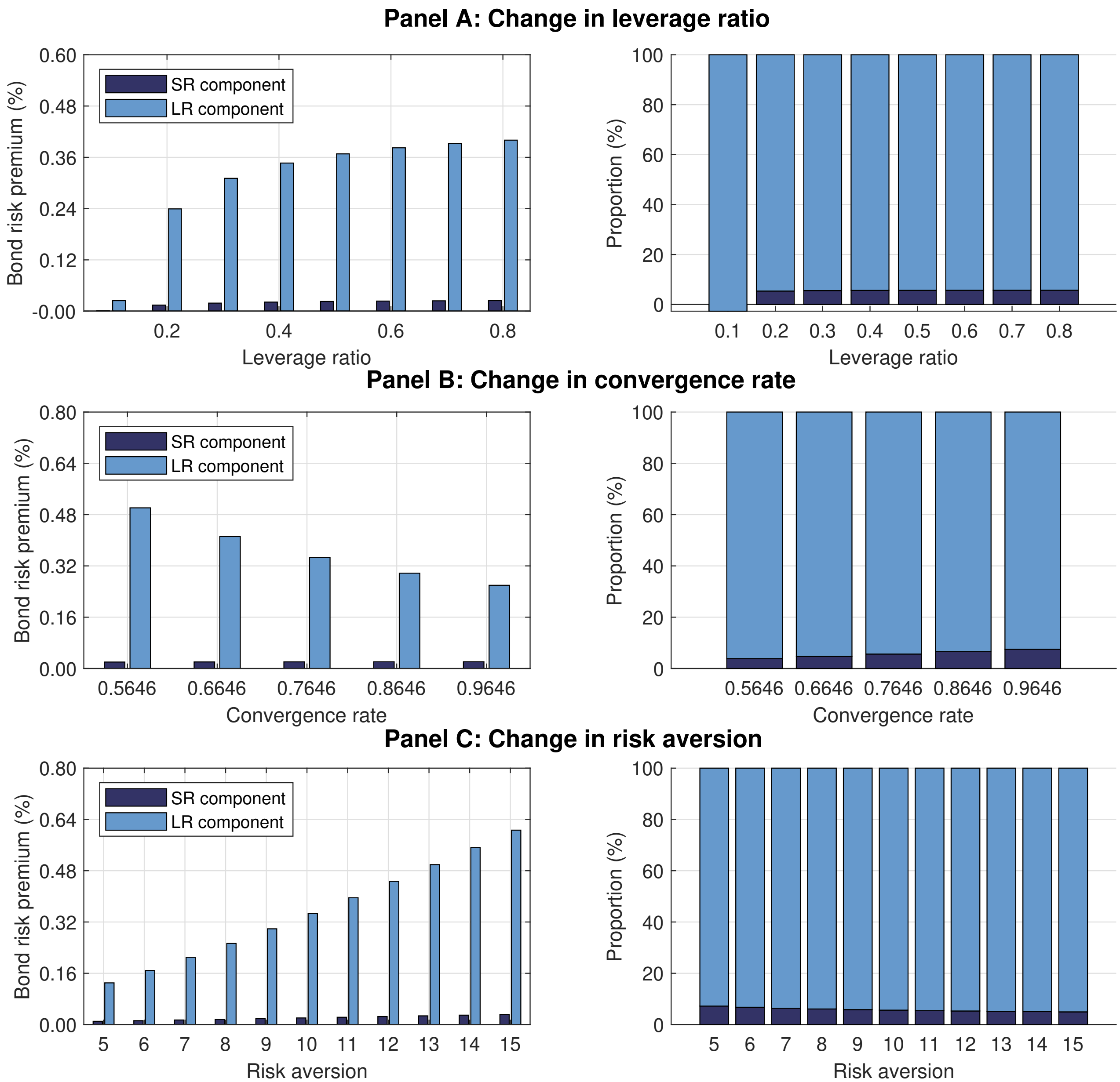

Figure 1. **Decomposition of bond risk premium**

This figure plots the decomposition of bond risk premium into the short-run risk component and the long-run risk component. The short-run risk component is computed by imposing no macroeconomic uncertainty. The long-run risk component is computed by subtracting the short-run risk component from the baseline model where both short- and long-run risk components are present. In Panel A, we vary the leverage ratio from 10% to 80%. In Panel B, we vary convergence rate to the long-run from 0.5646 to 0.9646 (0.7646 for the baseline), fixing the leverage ratio to 40%. In Panel C, we vary risk aversion γ from 5 to 15 (10 for the baseline), fixing the leverage ratio to 40%. Other parameter values are reported in Table A.1.

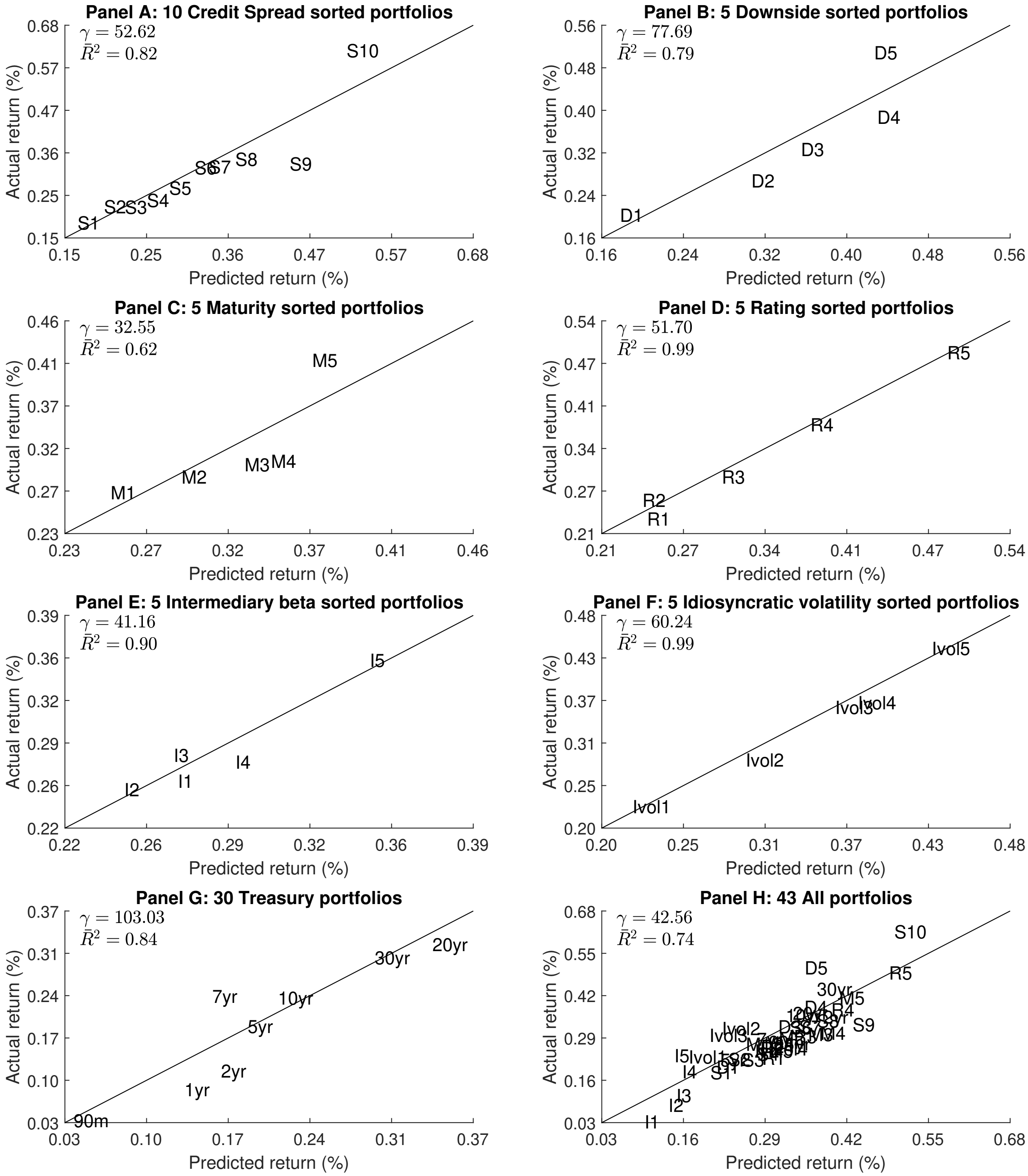

Figure 2. **Cross-sectional regression using GMM**

This figure plots the cross-section of actual average bond excess returns against the predicted average bond excess returns by the long-run consumption risk using the GMM estimation.

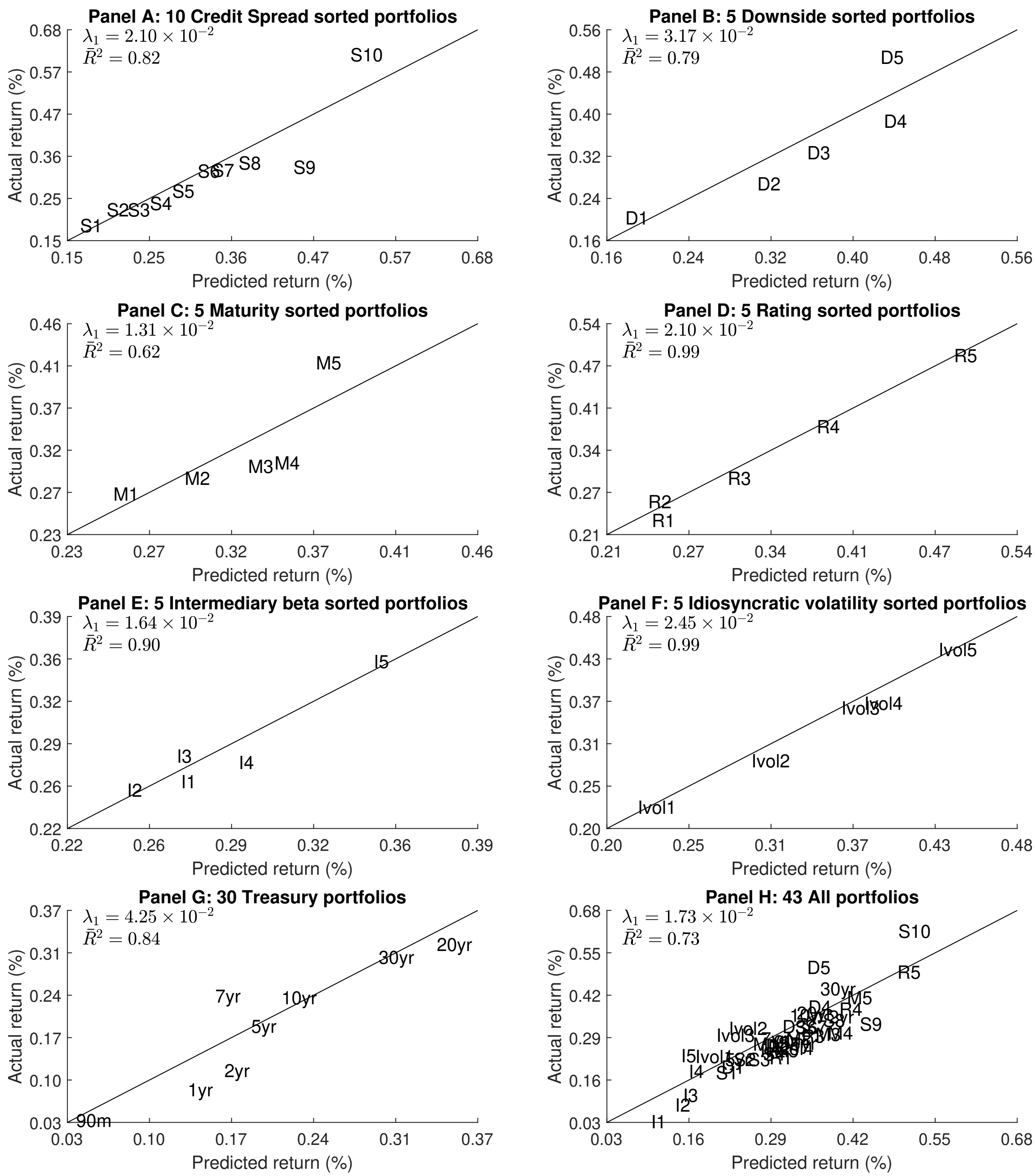

Figure 3. **Two-pass regression**

This figure plots the cross-section of actual average bond excess returns against the predicted average bond excess returns by the long-run consumption risk using two-pass regressions.

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A Appendix

A.1 Model of Bhamra, Kuehn, and Strebulaev (2010b)

A.1.1 Aggregate consumption and firm earnings

The economy is populated by a representative agent and a representative firm. The agent provides capital to the firm by investing in equity and bond, and also consumes the firm's output.

The dynamics of aggregate consumption C_t is exogenously given by

$$\frac{dC_t}{C_t} = g_{\nu_t} dt + \sigma_{C,\nu_t} dB_{C,t} \quad \forall \nu_t \in \{1, 2\} \tag{27}$$

where g_{ν_t} and σ_{C,ν_t} are the state-dependent expected consumption growth rate and consumption growth volatility, respectively. $dB_{C,t}$ is a standard Brownian motion shock to consumption.

The dynamics of aggregate earnings X_t is given by

$$\frac{dX_t}{X_t} = \theta_{\nu_t} dt + \sigma_X^{id} dB_{X,t}^{id} + \sigma_{X,\nu_t}^{s} dB_{X,t}^{s} \quad \forall \nu_t \in \{1, 2\} \tag{28}$$

where θ_{ν_t} is the state-dependent expected earnings growth rate, and σ_X^{id} and σ_{X,ν_t} are the idiosyncratic and systematic volatilities of the firm's earnings growth rate, respectively. The systematic earnings shock $dB_{X,t}^s$ is correlated with aggregate consumption shock: That is, $dB_{C,t} dB_{X,t}^s = \rho_{XC} dt$. In this economy, the long-run risk arises from slowly time-varying macroeconomic conditions. The first and second moments of consumption and earnings growth vary over time with persistent changes in the state of the economy. The state switches according to a two-state Markov chain defined by λ_{ν_t}, which is the probability per unit time of the economy leaving state ν_t.

A.1.2 Preferences

The representative agent has Epstein-Zin-Weil preferences. This is to ensure the long-run risk is priced by separating risk aversion from the elasticity of intertemporal substitution. Consequently, the representative agent's state-price density is given by

$$\pi_t = (\beta e^{-\beta t})^{\frac{1-\gamma}{1-\frac{1}{\psi}}} C_t^{-\gamma} \left(p_{C,t} e^{\int_0^t p_{C,s}^{-1} ds}\right)^{-\frac{\gamma - \frac{1}{\psi}}{1-\frac{1}{\psi}}} \tag{29}$$

where β is the rate of time preference, γ is the coefficient of relative risk aversion (RRA), ψ is the elasticity of intertemporal substitution (EIS), and $p_{C,t}$ is the price-consumption ratio. The representative agent cares about the rate of news arrival given by $p = \lambda_1 + \lambda_2$. The long-run probability of being in each state is given by $(f_1, f_2) = (\lambda_2/p, \lambda_1/p)$.

A.1.3 Asset prices

The debt value B_{ν_t} is the present value of a perpetual coupon stream c until default occurs at a random stopping time τ_D plus the present value of the recovered firm asset liquidation where α_{ν_t} is the state-dependent asset recovery rate.

$$B_{\nu_t} = E_t[\int_t^{\tau_D} \frac{\pi_s}{\pi_t} c ds|\nu_t] + E_t[\frac{\pi_{\tau_D}}{\pi_t}\alpha_{\tau_D} A_{\tau_D}|\nu_t] \tag{30}$$
$$= \frac{c}{r_{P,\nu_t}}(1 - \sum_{\nu_D=1}^{2} l_{D,\nu_t,\nu_D} q_{D,\nu_t,\nu_D}) \quad \forall \nu_t \in \{1,2\}$$

where r_{P,ν_t} is the discount rate for a riskless perpetuity, l_{D,ν_t,ν_D} is the loss ratio, and q_{D,ν_t,ν_D} is the Arrow-Debreu default claim.

The credit spread is given by

$$s_{\nu_t} = \frac{c}{B_{\nu_t}} - r_{P,\nu_t} = r_{p,\nu_t} \frac{\sum_{\nu_D=1}^{2} l_{D,\nu_t,\nu_D} q_{D,\nu_t,\nu_D}}{1 - \sum_{\nu_D=1}^{2} l_{D,\nu_t,\nu_D} q_{D,\nu_t,\nu_D}} \tag{31}$$

The conditional levered equity risk premium in state ν_t is

$$\mu_{R,\nu_t} - r_{\nu_t} = \gamma \rho_{XC} \sigma_{R,\nu_t}^{B,s} \sigma_{C,\nu_t} + \Pi_{\nu_t} \quad \forall \nu_t \in \{1,2\} \tag{32}$$

where $\sigma_{R,\nu_t}^{B,s} = \frac{\partial ln S_{\nu_t}}{\partial ln X_t} \sigma_{X,\nu_t}^{s}$ is the systematic volatility of stock returns caused by Brownian shocks. The first term is the risk compensation associated with the short-run risk. The second term is the long-run risk component (jump risk premium) which stems from uncertainty in states, which is given by $(\Pi_1, \Pi_2) = ((1-\omega^{-1})(\frac{S_2}{S_1} - 1)\lambda_1, (1-\omega)(\frac{S_1}{S_2} - 1)\lambda_2)$. ω measures the size of the jump in the state-price density when the economy shifts from state 2 to state 1: $\omega = \frac{\pi_t}{\pi_{t-}}|_{\nu_{t-}=2,\nu_t=1}$. Its size depends on the representative's preference for resolving intertemporal risk: $\omega > 1$ ($\omega < 1$) if $\gamma > 1/\psi$ ($\gamma < 1/\psi$) and $\omega = 1$ if $\gamma = 1/\psi$. If macroeconomic conditions do not vary, then intertemporal risk is eliminated. In this case, $\omega = 1$ and therefore the long-run risk component becomes zero i.e., $\Pi_{\nu_t} = 0$.

Stock value S_{ν_t} is the after-tax discounted value of future earnings X_t less coupon payment until bankruptcy.

$$S_{\nu_t} = (1-\eta) E_t[\int_t^{\tau_D} \frac{\pi_s}{\pi_t}(X_s - c) ds|\nu_t] \tag{33}$$
$$= A_{\nu_t}(X_t) - (1-\eta)\frac{c}{r_{P,\nu_t}} + \sum_{\nu_D=1}^{2} q_{D,\nu_t,\nu_D}[(1-\eta)\frac{c}{r_{P,\nu_D}} - A_{\nu_D}(X_{D,\nu_D})] \quad \forall \nu_t \in \{1,2\}$$

where $A_{\nu_t}(X_t) = \frac{(1-\eta)X_t}{r_{A,\nu_t}}$ is the liquidation value in state ν_t

Table A.1. **Model parameters**

This table reports the annualized parameter values used for the calibration. We use the parameter values from Bhamra, Kuehn, and Strebulaev (2010b) which are estimated using consumption and corporate earnings data from 1947Q1 to 2005Q4. Different from Bhamra, Kuehn, and Strebulaev (2010b), we use time-invariant consumption growth volatility and earnings growth volatility, and also the EIS equals 1, which is consistent with our empirical setting.

Parameter	Symbol	State 1	State 2
Consumption growth rate	g	0.0141	0.0420
Consumption growth volatility	σ_C	0.0101	0.0101
Earnings growth rate	θ	-0.0401	0.0782
Earnings growth volatility	σ_X^s	0.1012	0.1012
Idiosyncratic earnings growth volatility	σ_X^s	0.2258	0.2258
Correlation	ρ_{XC}	0.1998	0.1998
Actual long-run probabilities	f_i	0.3555	0.6445
Actual convergence rate to long run	p	0.7646	0.7646
Annual discount rate	β	0.01	0.01
Tax rate	η	0.15	0.15
Bankruptcy costs	$1 - \alpha_i$	0.30	0.10
Elasticity of intertemporal substitution	ψ	1	1
Risk aversion	γ	10	10

Table A.2. **Selection of factors and lag for consumption predictability**

Table A.2 shows the state vector which minimizes the AIC along with other candidate sets out of 196,605 candidate sets that we search for. Reported are the sets of state vector used to predict future consumption growth $c_{t+1} - c_t$ with R^2, adjusted-R^2, and AIC. Factors are estimated by the Principal Component Analysis based on 44 financial and macro economic variables. $F_{n,t}$ is the *n*-th factor from the PCA factors based on 44 pre-selected variables. $S_{m,t}$ is the surplus ratio defined as $\frac{1-\psi}{1-\psi^m} \sum_{j=0}^{m-1} \psi^j \Delta c_{t-j}$ with $\psi = 0.96$, following Wachter (2002) and Duffee (2005).

x_t	The number of lags	R^2	Adj.R^2	AIC
$F_{1,t}$	0	0.0001	-0.0014	-11.3414
$F_{1,t}$	1	0.0012	-0.0018	-11.3389
$F_{1,t}$	2	0.0089	0.0045	-11.3439
$F_{1,t}$	3	0.0109	0.0051	-11.3416
...				
...				
$F_{1,t}$, $F_{2,t}$, $F_{3,t}$, $F_{4,t}$, $F_{5,t}$, $F_{6,t}$	0	0.0429	0.0344	-11.3705
$F_{1,t}$, $F_{2,t}$, $F_{3,t}$, $F_{4,t}$, $F_{5,t}$, $F_{6,t}$	1	0.0596	0.0427	-11.3698
$F_{1,t}$, $F_{2,t}$, $F_{3,t}$, $F_{4,t}$, $F_{5,t}$, $F_{6,t}$	2	0.0758	0.0506	-11.3698
$F_{1,t}$, $F_{2,t}$, $F_{3,t}$, $F_{4,t}$, $F_{5,t}$, $F_{5,t}$	3	0.0787	0.0449	-11.3538
...				
$F_{3,t}$, $F_{5,t}$, $F_{9,t}$, $S_{9,t}$, $S_{24,t}$,$S_{36,t}$	0	0.0540	0.0456	-11.3822
$F_{3,t}$, $F_{5,t}$, $F_{9,t}$, $S_{9,t}$, $S_{24,t}$,$S_{36,t}$	1	0.1508	0.1356	-11.4719
$F_{3,t}$, $F_{5,t}$, $F_{9,t}$, $S_{9,t}$, $S_{24,t}$,$S_{36,t}$	2	0.1967	0.1748	**-11.5100**
$F_{3,t}$, $F_{5,t}$, $F_{9,t}$, $S_{9,t}$, $S_{24,t}$,$S_{36,t}$	3	0.2052	0.1761	-11.5015
...				
$S_{3,t}$, $S_{6,t}$, $S_{9,t}$, $S_{12,t}$, $S_{24,t}$,$S_{36,t}$	0	0.0282	0.0196	-11.3553
$S_{3,t}$, $S_{6,t}$, $S_{9,t}$, $S_{12,t}$, $S_{24,t}$,$S_{36,t}$	1	0.1072	0.0912	-11.4219
$S_{3,t}$, $S_{6,t}$, $S_{9,t}$, $S_{12,t}$, $S_{24,t}$,$S_{36,t}$	2	0.1446	0.1214	-11.4472
$S_{3,t}$, $S_{6,t}$, $S_{9,t}$, $S_{12,t}$, $S_{24,t}$,$S_{36,t}$	3	0.1461	0.1148	-11.4298
...				
...				
$F_{1,t}$, $F_{2,t}$, ... , $S_{24,t}$,$S_{36,t}$	0	0.0798	0.0577	-11.3806
$F_{1,t}$, $F_{2,t}$, ... , $S_{24,t}$,$S_{36,t}$	1	0.1849	0.1447	-11.4542
$F_{1,t}$, $F_{2,t}$, ... , $S_{24,t}$,$S_{36,t}$	2	0.2452	0.1878	-11.4841
$F_{1,t}$, $F_{2,t}$, ... , $S_{24,t}$,$S_{36,t}$	3	0.2684	0.1922	-11.4667

Table A.3. **Variance decomposition of selected factors**

Table A.3 presents the variance decomposition, defined as $\beta_z \frac{cov(x,z)}{var(x)}$ in percentage terms where $x = F_{3,t}$, $F_{5,t}$, and $F_{9,t}$ and z is one of 44 variables. *cay* is the cointegrating residual of consumption, financial wealth, and labor income from Lettau and Ludvigson (2001), *rrel* is the relative T-bill rate, defined as the 30-day T-bill rate minus its 12-month moving average. *yc* is the labor-to-consumption ratio. *ca* is the consumption-to-wealth ratio. *sc* is the stock market wealth to consumption ratio. *dp* is the dividend price ratio defined as the difference between the log of dividends and the log of prices. *dy* is the the dividend yield defined as the difference between the log of dividends and the log of lagged prices. *ep* is the earnings price ratio defined as the difference between the log of earnings and the log of prices. *de* is the dividend payout ratio defined as the difference between the log of dividends and the log of earnings. *svar* is the stock variance which is computed as sum of squared daily returns on the S&P 500. *bm* is the book-to-market ratio defined as the ratio of book value to market value for the Dow Jones Industrial Average. *ntis* is the net equity expansion which is the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. *lty* is the long term yield. *ltr* is the long term rate of returns. *tms* is the term spread defined as the difference between the long term yield on government bonds and the Treasury-bill. *dfy* is the default yield spread defined as the difference between BAA and AAA-rated corporate bond yields. *dfr* is the default return spread defined as the difference between long-term corporate bond and long-term government bond returns. *infl* is the growth rate of CPI. *ip* is the industrial production. *pdi* is the personal dividend income. *dspi* is the disposable personal income. *Unrate* is the unemployment rate. *leading* is the leading indicator. *crsp-vwret* is the return of CRSP-value weighted index. *Tre-30y*, *Tre-20y*, *Tre-10y*, *Tre-7y*, *Tre-5y*, *Tre-2y*, and *Tre-1y* are 30-, 20-, 10-, 7-, 5-, 2-, and 1-year Treasury bond rate. *Tre90day* and *Tre30day* are 90- and 30-day Treasury bill rate. *Ind-Cnsmr*, *Ind-Manuf*, *Ind-HiTec*, *Ind-Hlth*, and *Ind-Other* are 5-industry portfolios from Kenneth website, which denote consumer, manufacturing, Hi-Technologies, Health care, and others, respectively. *FMP-* are the Fama Maturity Portfolios with the following maturities: less than 12 months (*FMP-12m*), from 13 to 24 months (*FMP-24m*), from 25 to 36 months (*FMP-36m*), from 37 to 48 months (*FMP-48m*), from 49 to 60 months (*FMP-60m*), from 61 to 120 months (*FMP-120m*).

	Variables	$F_{3,t}$	$F_{5,t}$	$F_{9,t}$
1	*cay*	0.237	0.908	12.693
2	*rrel*	0.895	1.305	1.273
3	*yc*	0.107	5.325	0.389
4	*ca*	0.013	2.736	0.998
5	*sc*	0.032	4.199	0.773
6	*dp*	0.011	2.872	0.042
7	*dy*	0.355	1.933	0.589
8	*ep*	0.000	0.000	0.000
9	*de*	0.109	0.231	4.663
10	*svar*	2.821	0.686	11.845
11	*bm*	0.013	1.061	0.180
12	*ntis*	0.013	8.933	2.560
13	*lty*	0.043	0.718	0.322
14	*ltr*	0.154	2.790	1.903
15	*tms*	0.321	7.354	7.748
16	*dfy*	0.299	1.817	0.100
17	*dfr*	2.640	1.737	10.373
18	*infl*	0.061	2.564	3.528
19	*ip*	0.398	6.839	0.234
20	*pdi*	0.004	2.527	4.836
21	*dspi*	0.187	3.234	5.917
22	*Unrate*	0.692	4.106	5.603
23	*leading*	0.152	3.939	1.397
24	*crsp-vwret*	17.737	0.003	0.219
25	*Tre-30y*	0.320	3.484	2.858
26	*Tre-20y*	0.179	2.918	1.946
27	*Tre-10y*	0.105	1.478	0.232
28	*Tre-7y*	0.181	0.442	0.035
29	*Tre-5y*	0.194	0.045	0.663
30	*Tre-2y*	0.052	1.159	1.967
31	*Tre-1y*	0.001	3.439	1.307

32	*Tre-90day*	0.017	5.825	0.826
33	*Tre-30day*	0.026	4.847	2.631
34	*Ind-Cnsmr*	15.471	0.009	0.465
35	*Ind-Manuf*	14.933	0.020	0.007
36	*Ind-HiTec*	13.950	0.002	0.272
37	*Ind-Hlth*	11.140	0.035	2.534
38	*Ind-Other*	15.667	0.011	0.142
39	*FMP-12m*	0.002	5.289	0.099
40	*FMP-24m*	0.016	2.016	1.814
41	*FMP-36m*	0.061	0.663	1.858
42	*FMP-48m*	0.112	0.092	1.317
43	*FMP-60m*	0.166	0.003	0.744
44	*FMP-120m*	0.116	0.402	0.096

Table A.4. **VAR estimation**

Panel A reports the VAR estimation with the consumption growth and the selected state vector. The system of equations is estimated using OLS equation by equation. $F_{n,t}$ is the n-th factor from the PCA factors based on 44 pre-selected variables. $S_{m,t}$ is the surplus ratio defined as $\frac{1-\psi}{1-\psi^m}\sum_{j=0}^{m-1}\psi^j \Delta c_{t-j}$ with $\psi = 0.96$, following Wachter (2002) and Duffee (2005). Panel B reports the predictive OLS regression results for the ten credit spread sorted portfolios using the selected state vector. $r^{S1}_{t+1} - r^f_t$ denotes the monthly excess returns of the lowest credit spread bonds. $r^{S10}_{t+1} - r^f_t$ denotes the monthly excess returns of the highest credit spread bonds. Standard errors based on Newey and West (1987) are reported in parentheses. The lag for the standard errors is automatically selected based on Newey and West (1994). *,**, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. In Panel A, time period spans from April 1962 to December 2018. In Panel B, time period spans from January 1974 to June 2017.

	x_t						Constant	Adj.R^2	N
Dep. var.	$F_{3,t}$	$F_{5,t}$	$F_{9,t}$	$S_{9,t}$	$S_{24,t}$	$S_{36,t}$			
Panel A: VAR estimation									
$c_{t+1} - c_t$	1.8×10^{-4}***	6.9×10^{-4}***	-4.0×10^{-4}**	-0.2075	-3.1629**	-1.6705	5.5×10^{-4}*	0.175	681
	(5.0×10^{-5})	(1.8×10^{-4})	(1.6×10^{-4})	(0.4655)	(1.4570)	(1.7421)	(3.1×10^{-4})		
$F_{3,t+1}$	0.1701***	0.3864**	-0.5443***	414.25	1.0×10^{3}	-2.2×10^{3}*	-	0.048	681
	(0.0434)	(0.1546)	(0.1687)	(295.19)	(786.65)	(1.3×10^{3})			
$F_{5,t+1}$	0.0156	0.4220***	-0.2083***	93.882	261.12	-441.44	-	0.631	681
	(0.0246)	(0.0552)	(0.0606)	(110.08)	(345.69)	(505.41)			
$F_{9,t+1}$	-0.0550*	-0.1487**	0.3425***	53.767	411.98	-670.80	-	0.285	681
	(0.0283)	(0.0719)	(0.0817)	(127.16)	(401.78)	(548.52)			
$S_{9,t+1}$	2.3×10^{-5}***	9.0×10^{-5}***	-7.4×10^{-5}**	0.5394***	-0.2781	0.5491**	-	0.841	681
	(8.1×10^{-6})	(3.2×10^{-5})	(3.1×10^{-5})	(0.0703)	(0.2306)	(0.2527)			
$S_{24,t+1}$	1.1×10^{-5}***	4.3×10^{-5}***	-2.7×10^{-5}**	0.0060	0.5233***	0.1099	-	0.944	681
	(3.3×10^{-6})	(1.2×10^{-5})	(1.1×10^{-5})	(0.0349)	(0.1075)	(0.1313)			
$S_{36,t+1}$	9.5×10^{-6}***	3.5×10^{-5}***	-1.9×10^{-5}**	0.0032	-0.0512	0.6864***	-	0.959	681
	(2.9×10^{-6})	(9.6×10^{-6})	(9.1×10^{-6})	(0.0268)	(0.0773)	(0.0912)			
Panel B: Predictive power for ten credit spread sorted portfolio returns									
$r^{S1}_{t+1} - r^f_t$	-2.7×10^{-4}	0.0020**	-0.0022***	-0.7286	-0.4274	-1.0021	0.0035*	0.033	522
	(2.3×10^{-4})	(8.0×10^{-4})	(7.7×10^{-4})	(2.4260)	(7.7088)	(11.544)	(0.0019)		
$r^{S2}_{t+1} - r^f_t$	-4.8×10^{-4}	0.0026**	-0.0025**	0.1886	1.0198	-8.5179	0.0061**	0.036	522
	(3.5×10^{-4})	(0.0011)	(0.0011)	(3.4198)	(11.432)	(17.733)	(0.0026)		
$r^{S3}_{t+1} - r^f_t$	-5.7×10^{-4}	0.0032**	-0.0026*	0.2049	4.1615	-12.344	0.0072**	0.034	522
	(4.0×10^{-4})	(0.0015)	(0.0014)	(3.9466)	(12.427)	(19.620)	(0.0031)		
$r^{S4}_{t+1} - r^f_t$	-3.6×10^{-4}	0.0035**	-0.0030*	-0.2066	7.2650	-15.211	0.0074**	0.031	522
	(4.4×10^{-4})	(0.0017)	(0.0017)	(4.2399)	(13.214)	(20.645)	(0.0033)		
$r^{S5}_{t+1} - r^f_t$	-3.2×10^{-4}	0.0040**	-0.0035*	0.1003	8.0888	-14.713	0.0081**	0.034	522
	(4.8×10^{-4})	(0.0020)	(0.0019)	(4.5301)	(13.950)	(21.433)	(0.0036)		
$r^{S6}_{t+1} - r^f_t$	-9.0×10^{-5}	0.0036*	-0.0034*	0.7652	10.305	-18.534	0.0079**	0.024	522
	(4.9×10^{-4})	(0.0020)	(0.0020)	(4.8059)	(14.190)	(22.114)	(0.0037)		
$r^{S7}_{t+1} - r^f_t$	2.1×10^{-4}	0.0044*	-0.0043*	-0.2133	7.1696	-12.586	0.0088**	0.037	522
	(5.4×10^{-4})	(0.0025)	(0.0023)	(4.7211)	(14.360)	(21.846)	(0.0039)		
$r^{S8}_{t+1} - r^f_t$	5.7×10^{-4}	0.0044*	-0.0049*	-1.2832	7.0155	-7.5607	0.0083**	0.044	522
	(6.2×10^{-4})	(0.0025)	(0.0027)	(4.5066)	(14.253)	(21.640)	(0.0040)		
$r^{S9}_{t+1} - r^f_t$	0.0011	0.0044	-0.0048	-0.9149	11.064	-10.814	0.0090**	0.056	522
	(7.7×10^{-4})	(0.0029)	(0.0034)	(4.6025)	(14.508)	(21.946)	(0.0046)		
$r^{S10}_{t+1} - r^f_t$	0.0032**	0.0058	-0.0055	1.1416	17.778	-27.170	0.0135*	0.088	522
	(0.0013)	(0.0036)	(0.0050)	(5.1820)	(15.667)	(24.470)	(0.0080)		

Table A.5. **Descriptive statistics for the VAR**

This table reports the number of observations, mean, standard deviation, and percentiles of the long-run consumption risk measured using the VAR and its component. The long-run risk is measured as $(E_{t+1} - E_t)\sum_{s=0}^{\infty}\beta^s(c_{t+1+s} - c_{t+s}) = \epsilon_{t+1}^{SR} + \epsilon_{t+1}^{LR}$ where $c_{t+1} - c_t = \mu_c + G'x_t + \epsilon_{t+1}^{SR}$, $x_{t+1} = Ax_t + \epsilon_{t+1}^{x}$, and $\epsilon_{t+1}^{LR} = \beta G'(I - \beta A)^{-1}\epsilon_{t+1}^{x}$, following Hansen et al. (2007) and Hansen, Heaton, and Li (2008). Time period spans from February 1973 to June 2017.

				Percentiles (%)						
	N	Mean (%)	SD (%)	1st	5th	25th	50th	75th	95th	99th
$(E_{t+1} - E_t)\sum_{s=0}^{\infty}\beta^s(c_{t+1+s} - c_{t+s})$	533	0.04	1.69	-4.15	-2.79	-0.83	0.02	0.94	2.93	4.21
ϵ_{t+1}^{SR}	533	-0.01	0.29	-0.77	-0.48	-0.15	0.00	0.15	0.45	0.74
ϵ_{t+1}^{LR}	533	0.04	1.59	-4.18	-2.40	-0.76	0.01	0.88	2.54	4.24

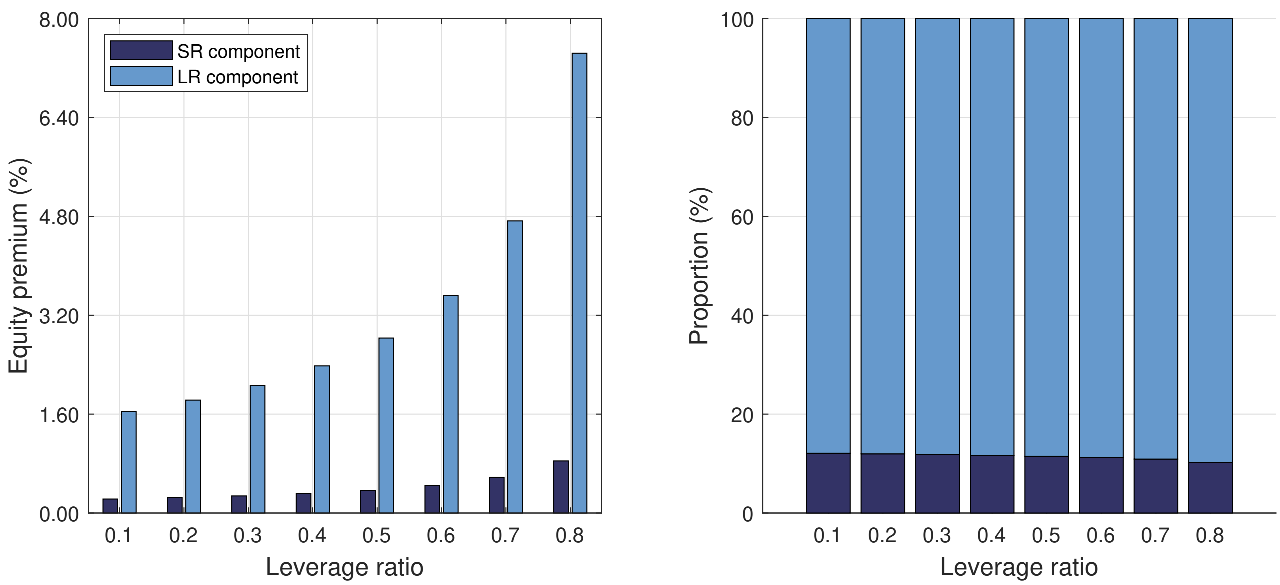

Figure A.1. **Decomposition of equity premium with leverage ratio**
This figure plots the decomposition of equity risk premium into the short-run risk component and the long-run risk component. The short-run risk component is computed by imposing no macroeconomic uncertainty. The long-run risk component is computed by subtracting the short-run risk component from the baseline model where both short- and long-run risk components are present. We vary the leverage ratio from 10% to 80%. Other parameter values are reported in Table A.1.