A One-Factor Model of Corporate Bond Premia [1]

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Abstract

A one-factor model based on long-run consumption growth explains the risk premiums on corporate bond portfolios sorted on credit rating, credit spreads, downside risk, idiosyncratic volatility, long-term reversals, maturity, and sensitivity to the financial intermediary capital factor. The estimated risk-aversion coefficient is lower when we use the consumption growth of wealthy households over a longer horizon as a risk factor, and a model with a 20-quarter horizon yields a risk-aversion coefficient of 15, a value similar to the one estimated from equity portfolios.

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1 Introduction

Does macroeconomic risk explain expected returns on corporate bonds? Despite the size of the corporate bond market, there is no agreement in the literature on economic determinants of corporate bond risk premiums. In this article, we use large panel data of bond returns and show that wealthy households' consumption growth accumulated over the long horizon can explain the cross-sectional variation in risk premium.

But before examining the data, why in the first place should consumption risk explain corporate bond risk premiums? First, there is evidence in the literature that long-run consumption risk explains the aggregate credit spreads (e.g. Bhamra, Kuehn, and Strebulaev (2010b), Chen (2010), and Kuehn, Schreindorfer, and Schulz (2021)). 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.

Second, Gilchrist and Zakrajšek (2012) empirically show that credit spreads are a strong predictor of economic growth. Thus, changes in credit spreads – roughly equivalent to bond returns – should also predict future consumption growth (which we confirm in the data), leading to comovement between bond returns and expected consumption growth. If investors have Epstein-Zin preferences, shocks to expected consumption growth carry a large price of risk, and thus assets that co-move with such shocks earn risk premiums. This evidence in the literature suggests that long-run consumption risk is a prominent candidate that explains corporate bond risk premiums.

However, the ability of long-run consumption risk to explain bond premiums is far from obvious due to an increasingly popular view that financial intermediaries rather than households are the marginal investors who price assets. According to this view, a household's consumption growth will not align with asset returns, and thus it does not explain risk premiums. In recent work, Haddad and Muir (2021) show that corporate credit is the most financially-intermediated asset class, suggesting that consumption risk may not matter for corporate bond returns. The tension between the two priors begs extensive empirical investigation into the ability of consumption risks in explaining corporate bond risk premiums, which is the focus of our paper.

In this article, we study whether or not a one-factor model based on long-run consumption risk explains variation in corporate bond risk premiums associated with a wide range of bond characteristics for the period 1973-2019. Specifically, we construct 7 sets of portfolios of corporate bonds sorted on credit spreads, credit rating, downside risk, idiosyncratic volatility, long-term reversal, maturity, sensitivity to the intermediary factor of He, Kelly, and Manela (2017) and use them as test assets. To measure long-run consumption risk, we simply accumulate consumption growth up to 24 quarters and calculate the covariance between portfolio returns and consumption growth.

Our one-factor model is motivated by the long-run risk model of Bansal and Yaron (2004) and Malloy, Moskowitz, and Vissing-Jørgensen (2009). Under several simplifying assumptions such as the unitary elasticity of intertemporal substitution (EIS), the model leads us to use cumulative consumption growth as a risk factor. We apply the Generalized Method of Moments (GMM) estimation of the model to the data, effectively running cross-sectional regressions of average excess returns on the covariance between the factor and excess returns. The long-run risk model allows us to interpret the slope coefficient of the regression as a risk-aversion coefficient of households, and to evaluate how plausible the model estimate is.

In testing the model, we use wealthy households' consumption from the Consumer Expenditure Survey (CEX) data in addition to aggregate consumption from the National Income and Product Account (NIPA) data. Though these wealthy households do not necessarily own corporate bonds directly, their consumption-savings choice is less likely to be constrained and thus their marginal utility is more likely to be aligned with asset returns. Therefore, with the CEX data, we can potentially measure consumption growth that is more relevant in explaining asset returns than the aggregate consumption data which partly reflects non-discretionary consumption.

In the data, long-run consumption risk explains a significant fraction of corporate bond risk premiums. When we use wealthy households' cumulative 20-quarter consumption growth as a risk factor, the cross-sectional R-squared is 0.80, while the risk-aversion coefficient is estimated at 15. This estimate is higher than the conventional level in an interval of 0.5 to 2, but lower than the estimates based on asset prices in the previous literature (e.g., Calvet and Czellar 2015). Notably, our estimate is similar to 10, the value used to calibrate the long-run risk model. Since the confidence interval ranges from 7.1 to 25.9, our estimate is statistically indistinguishable from 10.

Importantly, the estimated level of risk aversion is very similar to the one estimated from equities. This similarity implies that from our model's perspective, bonds and equities are priced consistently. That is, the model "solves" the credit spread puzzle in the cross section based on the empirically estimated parameters rather than on calibrated models.

In contrast, when we use aggregate consumption growth, the estimated risk-aversion coefficient is higher: it ranges from above 250 to 50 as we expand the horizon to cumulate the growth up to 24 quarters. At the horizon with the lowest risk-aversion estimate, the cross-sectional R-squared is 0.64, lower than the estimates using wealthy households' consumption.

These results suggest that, when corporate bond returns are low, consumption tends to fall as well. Importantly, the reaction of consumption persists over the medium horizon, and it is more pronounced for wealthy households' consumption. Corporate bonds with higher average returns, such as those with higher credit spreads, predict consumption more than those with lower average returns do. From a forward-looking investor's perspective, bonds whose return co-move with future consumption growth are regarded as risky, and thus command premiums to bear the risk. Consistent with the finding of Parker and Vissing-Jørgensen (2009), wealthy households' consumption is more sensitive to macroeconomic shocks than aggregate consumption is, and therefore we need a lower value of risk aversion to justify the cross-sectional variation in average corporate bond returns.

In order to compare the long-run consumption risk to other factors proposed in the literature, we regress the consumption-factor mimicking portfolio excess returns on the seven factors of Fama and French (1993, 2015), the intermediary-factor mimicking portfolio of He, Kelly, and Manela (2017), and the bond market, downside risk and credit risk factors of Bai, Bali, and Wen (2019). We find that our factor earns significant alphas against the existing factors, suggesting that the long-run consumption risk is not subsumed by the existing factors.

However, we find that the consumption risk factor does not explain corporate bond portfolios sorted by the Roll illiquidity measure, bond's age, issue size, as well as betas with respect to shocks to the aggregate bond illiquidity measure proposed by Hu, Pan, and

Wang (2013). This finding suggests that the consumption-based model is a powerful model in explaining default risk and macroeconomic uncertainty priced in corporate bonds, but not necessarily risk premiums arising from illiquidity, suggesting that the consumption-based model is complementary to the intermediary-based model which better explains risk premiums associated with liquidity.[2]

Our asset pricing tests address the concerns raised by Lewellen, Nagel, and Shanken (2010) on empirical methods because we test a one-factor model using 7 bond characteristics. Moreover, the performance of the long-run consumption-based model is robust to various changes in the specification of the tests. The main results hold when we (i) use the consumption of bondholders, (ii) use shocks to expectations for infinite-horizon consumption growth rate implied by a VAR as a risk factor, (iii) estimate the long-run risk model with various levels of elasticity of intertemporal substitution, (iv) allow asset returns to be not log-normally distributed, (v) use international corporate bonds as alternative test assets, and (vi) conduct asset pricing tests based on time-series regressions as in Fama and French (1993) and Barillas and Shanken (2018).

In summary, we contribute to the literature by demonstrating that consumption risk explains a cross-section of corporate bond risk premiums closely following the method established by Malloy, Moskowitz, and Vissing-Jørgensen (2009). Our results also suggest that it is possible to tame the factor zoo for corporate bonds, as the risk premium variation associated with well-known characteristics such as credit rating, downside risk, volatility, and long-term reversal can be well captured by a single macroeconomic factor.

[2] See Goldberg and Nozawa (2021) for the evidence of intermediary affecting bond liquidity and risk premiums.

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), Chung, Wang, and Wu (2019), Bali, Subrahmanyam, and Wen (2021b,a), Bretscher et al. (2021), and Bali et al. (2021) document different predictors of bond returns, while Kelly, Palhares, and Pruitt (2021) propose a reduced-form factor model. In particular, the papers closest to ours are He, Kelly, and Manela (2017) and Bai, Bali, and Wen (2019, 2021). These papers present different multi-factor models with different motivations to explain the cross-section of corporate bond returns. In contrast, our model uses only one risk factor and offers a more parsimonious explanation.

There is another strand of literature which incorporates consumption shocks in structural models of debt to price corporate credit spreads (e.g., Chen, Collin-Dufresne, and Goldstein 2008; Gourio 2013). In particular, Bhamra, Kuehn, and Strebulaev (2010b), Chen (2010), Elkamhi and Salerno (2020), and Kuehn, Schreindorfer, and Schulz (2021) calibrate the long-run risk models and show that the long-run risk is instrumental in explaining the aggregate credit spreads and equity risk premiums. Our study echoes the importance of the long-run risk not only for credit spreads but also for bond risk premiums.

Our paper also contributes to the literature that investigates the link between slow-moving components in consumption growth and a cross-section of asset returns, including Aït-Sahalia, Parker, and Yogo (2004), Bansal, Dittmar, and Lundblad (2005), Parker and Julliard (2005), Yogo (2006), Hansen, Heaton, and Li (2008), Malloy, Moskowitz, and Vissing-Jørgensen (2009), Bansal, Kiku, and Yaron (2009), Elkamhi and Jo (2019), and Bryzgalova and Julliard (2019). Ferson, Nallareddy, and Xie (2013) study the performance of the long-run risk model with the NIPA consumption data and conclude that it does not explain the low-grade corporate bond index well. In contrast, we use different consumption data and show that the model explains a broad cross-section of corporate bonds well.

Finally, this paper relates to the role of heterogeneous households and asset prices. Mankiw and Zeldes (1991), Basak and Cuoco (1998), Guvenen (2009), Chien, Cole, and Lustig (2016), Elkamhi and Jo (2019), Lettau, Ludvigson, and Ma (2019), and Toda and Walsh (2019) show that accounting for heterogeneity in various agents' consumption helps explain risk premiums. In this paper, we directly measure wealthy households' consumption growth instead of using indirect proxies (such as capital share), and apply it to a wide cross-section of corporate bonds.

The rest of the paper is organized as follows: in Section 2, we discuss data and the empirical application of the long-run risk model; in Section 3, we present the empirical results; in Section 4, we present several extensions of the empirical analysis; and in Section 5, we provide concluding remarks.

2 Data and methodology

2.1 Data

2.1.1 Consumption data

We use the consumption of wealthy households from the CEX data from March 1984 to December 2019. We calculate consumption growth in the following way.[3] First, expenditures for nondurables and services from the CEX consumption categories are used to match the definition of nondurables and services in NIPA. Second, to adjust the seasonality of

[3]The CEX is a nationwide household survey conducted by the U.S. Bureau of Labor Statistics (BLS), designed to provide detailed data on spending, income, demographics, and asset holding information. The data is publicly available at https://www.bls.gov/cex/.

consumption, we regress the change in real per capita household consumption on a set of seasonal dummies and use the residual as our consumption growth measure. Finally, for each month, we compute the average consumption growth rates across wealthy households. Wealthy households are defined as the top 30% of asset holders based on their beginning-of-quarter holding of stocks, mutual funds, and bonds. The cutoffs for being in the top 30% are defined by the calendar year. The CEX data does not allow us to separate the ownership of bonds from other financial assets. This is not an issue for our purpose since we choose those households not because they hold corporate bonds directly, but because we wish to examine the consumption of households whose intertemporal consumption decision is less likely to be constrained.

In the CEX data, a sample household is interviewed every three months over five times. Also, the CEX surveys different sets of households every month by including new households and dropping old households who finish the last interview. Therefore, we observe the quarterly consumption growth rates at a monthly frequency for the consumption of wealthy households. Section I.G of the Internet Appendix provides more details on the CEX data and sample selection criteria.

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 February 1959 to December 2019.[4] Real per capita growth rates are calculated by deflating nominal values using the 2012 dollars and subtracting the log population growth rate, using a monthly population from NIPA Table 2.6.

[4] We also use the most recent samples of 2020 and find that our main results are robust to the extended sample periods in which consumption level significantly drops due to the pandemic. This result is reported in Table IA1 of the Internet Appendix.

Table 1 presents the summary statistics for CEX/NIPA cumulative discounted S-quarter consumption growth $\sum_{s=0}^{S-1} \delta^s(c_{t+s+1} - c_{t+s})$ with S=1,. . ., 20, where the subjective discount rate δ is set to $0.95^{1/4}$. In Panel A, the standard deviation of quarterly consumption growth ($S = 1$) of CEX wealthy households is 8.3%, while the standard deviation of the discounted cumulative 20-quarter consumption growth is 8.8%. For the NIPA aggregate consumption growth, the standard deviation is lower at 0.4% for quarterly growth but increases to 3.5% for cumulative 20-quarter growth.

For a consumption-based model to work, the factor needs to be not only volatile but also co-move with asset returns. To understand the sensitivity of consumption growth to asset returns, we regress cumulative S-quarter consumption growth on quarterly returns on the value-weighted bond market portfolios. Panel B of Table 1 reports the estimated slope coefficients of the regressions. The sensitivity of wealthy households' consumption growth to bond returns is 0.26 when $S = 1$, which increases modestly to 0.38 when $S = 20$. The sensitivity increases for a longer horizon because bond returns do not only co-move with consumption growth, but also predict future consumption growth. In contrast, the sensitivity of NIPA aggregate consumption growth is about zero when $S = 1$, and increases to 0.13 when $S = 20$. Therefore, the long-run growth rate for wealthy households' consumption is three times as sensitive to aggregate shocks as the NIPA aggregate consumption growth. As explained in the next section, this high sensitivity is the key to the performance of a consumption-based model in explaining corporate bond risk premiums. Furthermore, in Internet Appendix II, we study the behavior of wealthy households' consumption over the business cycle and find that wealthy households' consumption shock is more sensitive to macroeconomic uncertainty of Jurado, Ludvigson, and Ng (2015) than the aggregate consumption is.

2.1.2 Bond return data

For data on corporate bond returns, we mostly follow Nozawa (2017). We construct the panel data of clean prices on corporate bonds from the Lehman Brothers Fixed Income Database, the Mergent FISD/NAIC Database, TRACE, and DataStream, spanning returns from February 1973 to December 2019. For the empirical test below, we use as long time-series data as possible given the availability of bond returns and consumption data, and thus the end of the sample period is determined by the shorter of the two. For example, in our main results where we use a 20-quarter consumption growth rate as a risk factor, our return sample ends in March 2015 which is determined by the availability of consumption data. When there are overlaps among the four databases, we prioritize them in the following order: the Lehman Brothers Fixed Income Database, TRACE, Mergent FISD/NAIC, and DataStream. Detailed descriptions of these databases as well as summary statistics of monthly returns are provided in the Internet Appendix I.

We remove bonds with floating rates and with option features other than callable bonds. Furthermore, we apply two 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.

Based on clean prices and accrued interest in the data, we calculate a monthly return on a corporate bond in month t as

$$R_t = \frac{P_t + AI_t + Coupon_t}{P_{t-1} + AI_{t-1}} - 1, \tag{1}$$

where P_t is month-t clean price, AI_t is accrued interest for the bond at the end of month t, and $Coupon_t$ is coupon paid during month t.

Using this panel data of corporate bond returns, we form 7 sets of portfolios. First, Nozawa (2017) shows that credit spreads are a strong predictor of the cross-section of corporate bond returns. Based on his finding, He, Kelly, and Manela (2017) test their intermediary asset pricing model using 10 portfolios sorted on credit spreads. Thus, every month, we form 10 value-weighted portfolios based on the average credit spreads between months $t-12$ and $t-1$. We put a one-month lag between the period where we observe the signal (the average of 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, idiosyncratic volatility, and long-term reversals. 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[5]) and find that these characteristics are a strong predictor of corporate bond returns. Furthermore, Gebhardt, Hvidkjaer, and Swaminathan (2005) use the bond's maturity as a predictor variable, while Chung, Wang, and Wu (2019) use idiosyncratic volatility of bond returns.[6] More recently, Bali, Subrahmanyam, and Wen (2021a) propose long-term

[5]We impose the minimum number of observations at 24 months.

[6]To compute idiosyncratic volatility, we run regressions of bond returns on the 5 factors of Fama and French (2015) over the 36-month rolling window (with the minimum number of observations of 24 months), and calculate the standard deviation of the regression residuals.

reversals (measured by negative of cumulative 3-year returns from $t-48$ to $t-12$) as a corporate bond risk factor. Thus, every month, we sort bonds into quintiles based on these characteristics. Bai, Bali, and Wen (2019) also show that liquidity and short-term reversals predict corporate bond returns. Since liquidity is likely to be a different source of risk premiums than default-related factors that we focus on, we study it separately in Section 4.4.[7]

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.[8] We then sort bonds every month into 5 value-weighted portfolios based on the pre-formation betas.

To summarize, we have 7 sets of portfolios sorted on credit spreads, credit rating, downside risk, idiosyncratic volatility, intermediary factor-betas, long-term reversal, and maturity, starting around 1973 and ending in December 2019.[9] In the empirical analysis, we use quarterly returns at the monthly frequency obtained by cumulating monthly portfolio returns.

[7]We do not use short-term reversal, as Bai, Bali, and Wen (2019) show that it is not a source of systemic risk and likely to be driven by the market microstructure noise in the data.

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

[9]The exact starting month varies across portfolios. The credit rating and maturity portfolios start in February 1973, the credit spread portfolios start in April 1973, intermediary factor-beta portfolios start in February 1974, downside risk and idiosyncratic volatility portfolios start in February 1975, and long-term reversal portfolios start in February 1977.

2.2 Methodology

We follow Malloy, Moskowitz, and Vissing-Jørgensen (2009) in estimating the consumption-based model. In the model, an agent in the economy has recursive preferences of a form,

$$V_t = \left[(1-\delta) C_t^{1-\frac{1}{\rho}} + \delta \left[E_t(V_{t+1}^{1-\gamma}) \right]^{\frac{1-\frac{1}{\rho}}{1-\gamma}} \right]^{\frac{1}{1-\frac{1}{\rho}}}, \tag{2}$$

where C_t is consumption in month t, ρ is the elasticity of intertemporal substitution, 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),

$$c_{t+1} - c_t = \mu_c + U_c x_t + \eta_0 w_{t+1}, \tag{3}$$

$$x_{t+1} = G x_t + H w_{t+1}. \tag{4}$$

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 I. Eq. (3) and (4) imply that log consumption growth can be expressed as a stationary moving-average process of the form,

$$c_{t+1} - c_t = \mu_c + \sum_{s=0}^{\infty} \eta_s w_{t+1-s} \equiv \mu_c + \eta(L) w_{t+1}. \tag{5}$$

Following Hansen, Heaton, and Li (2008) and Malloy, Moskowitz, and Vissing-Jørgensen (2009), we focus on a special case in which EIS is one in the main results. This assumption allows us to express the stochastic discount factor (SDF) derived from the preferences in (2) as a log-linear function of state variables, and considerably simplifies it. We then present results when EIS differs from one as a robustness check later in Section 3.3.

Under the assumption EIS=1, the log stochastic discount factor is,

$$s_{t+1} = \log\delta - [\mu_c + \eta(L)w_{t+1}] + (1-\gamma)\eta(\delta)w_{t+1} - \frac{1}{2}(1-\gamma)^2\eta(\delta)^2, \tag{6}$$

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

$$\approx \log\delta + (1-\gamma)\left[(E_{t+1} - E_t)\sum_{s=0}^{\infty}\delta^s(c_{t+1+s} - c_{t+s})\right] - \frac{1}{2}(1-\gamma)^2\eta(\delta)^2. \tag{8}$$

In the last line, we drop the contemporaneous consumption growth $c_{t+1} - c_t$ because it is known to play a minimal 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 investors' expectations for the future consumption growth rate. With the Epstein-Zin preferences, such a shock affects investors' marginal utility of consumption at $t + 1$, and thus should be reflected in asset prices.

Despite its name, the long-run risk model applies to assets with any maturity as long as their returns co-move with expected consumption growth. Consider a bond with 2 years to maturity: this bond can command large premiums if its one-quarter return co-moves well with long-run consumption growth. Thus, even though the bond matures way before "long run", the model can generate risk premiums for short-term assets whose returns predict consumption growth.

With a valid stochastic discount factor, the Euler equation $E[S_{t+1}R_{i,t+1}] = 1$ must hold when the agent's savings-consumption decision is unconstrained. In the main analysis, we make an additional assumption that a return $R_{i,t+1}$ is lognormally distributed, but we relax this assumption later in Section 4. Under the lognormality assumption, we derive the unconditional Euler equation for a log return on asset i in excess of the risk-free rate of return,

$$E[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} = -cov(s_{t+1}, r_{i,t+1} - r_{f,t}). \tag{9}$$

We plug the log stochastic discount factor in (8) into (9) and obtain,

$$\begin{aligned} & E[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} \\ & \approx (\gamma - 1)cov\left((E_{t+1} - E_t)\sum_{s=0}^{\infty}\delta^s(c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}\right), \qquad (10) \\ & = (\gamma - 1)cov\left(\sum_{s=0}^{\infty}\delta^s(c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}\right) \\ & - (\gamma - 1)cov\left(E_t\sum_{s=0}^{\infty}\delta^s(c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}\right). \qquad (11) \end{aligned}$$

where $r_{i,t+1}$ is a 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}.

Malloy, Moskowitz, and Vissing-Jørgensen (2009) test a simplified version of the Euler equation in (11) 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:

$$\begin{aligned} & E[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} \\ & \approx (\gamma - 1)cov\left(\sum_{s=0}^{\infty}\delta^s(c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}\right). \qquad (12) \end{aligned}$$

Eq. (12) implies that, in order to obtain a low risk-aversion coefficient, we need a large covariance between asset returns and long-run consumption growth.

Malloy, Moskowitz, and Vissing-Jørgensen (2009) truncate the summation over the infinite horizon in (12) up to S quarters, 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 the advantage of transparency. If we test (11), 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 a VAR specification and will be affected by estimation errors in a VAR model. The simplified model in (12) 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 (12) with finite S and then present the conditional model in (11) that captures shocks to expected consumption growth over the infinite horizon.

When testing the Euler equation in (11) using CEX consumption data, we use the average of log consumption growth across wealthy households, such that $c_{t+1}-c_t=\frac{1}{H_t}\sum_h(c_{h,t+1}-c_{h,t})$. This procedure implies that we start from the Euler equation for each household, and then aggregate it across households without using the representative agent framework.

Wealthy households typically do not own corporate bonds directly, but hold them through mutual funds (Bai, Bali, and Wen (2021)). This does not automatically invalidate the link between their consumption growth and bond risk premiums. In classic portfolio theories, optimal holdings can be described as a combination of several portfolios (such as a tangency portfolio and a risk-free asset) under certain conditions,[10] which is called "mutual

[10]See, for example, Ingersoll (1987).

fund" separation theorems. If these funds are mean-variance efficient, then their returns and owners' consumption can serve as a valid risk factor irrespective of whether the households own bonds directly or through mutual funds. Importantly, when we examine the consumption risk of bonds, we do not assume that wealthy households' consumption decision "moves" corporate bond prices through fire sales and purchases. Rather, we view unobservable macroeconomic shocks as affecting both households' consumption decisions and bond returns simultaneously, and we use the resulting correlation as a measure of risk.

3 Empirical results

3.1 Measuring long-run consumption risk

Before estimating the Euler equation in (12), we dissect the long-run consumption risk of corporate bond portfolios using the covariance between long-run consumption growth and quarterly returns on bond portfolios. To understand why the model works, we compare long-run risk with short-run risk,

$$\underbrace{cov\left(\sum_{s=0}^{S-1}\delta^s(c_{t+s+1}-c_{t+s}),r^e_{i,t+1}\right)}_{\text{Long run}}=\underbrace{cov\left(c_{t+1}-c_t,r^e_{i,t+1}\right)}_{\text{Short run}}+cov\left(\sum_{s=1}^{S-1}\delta^s(c_{t+s+1}-c_{t+s}),r^e_{i,t+1}\right). \tag{13}$$

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

The short-run risk 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 difference between the long-run and short-run risks comes from the predictability of future consumption growth with bond returns. If a higher return in quarter $t+1$ predicts higher consumption growth afterward, then this long-run risk is greater than the short-run risk.[11]

Table 2 presents average excess returns, short-run covariance $\hat{cov}(c_{t+1} - c_t, r_{i,t+1} - r_{f,t})$, and long-run covariance, measured by the discounted 20-quarter cumulative consumption growth of CEX wealthy households $\hat{cov}(\sum_{s=0}^{19} \delta^s (c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_t^f)$ for 40 portfolios we use as test assets. For all sorting variables, the long-run risk model generates a similar pattern in covariance as that in average excess returns. Specifically, the covariance with 20-quarter consumption growth increases nearly monotonically from the first quintile/decile to the last quintile/decile for all subsets of portfolios. The average excess returns for those portfolios increase similarly, suggesting that the long-run risk model not only generates large risk exposure, but also the pattern in risk exposure which matches that in average excess returns. Moreover, the difference in long-run covariance between the last and the first quintile/decile is larger than that in short-run covariance, underscoring the importance of long-run consumption risk.

Panel A of Figure 1 visualizes the information in Table 2, plotting average excess returns on the y-axis and covariance on the x-axis. The covariance is greater when we use wealthy households' consumption growth over the long horizon than short-run consumption growth, and thus the fitted line flattens. This implies that the return spread between the last and first quintile/decile predicts their consumption growth. Panel B of Figure 1 shows the same plot but using NIPA aggregate consumption growth over 1 and 8 quarters instead of CEX wealthy households' consumption. We treat 8 quarters as a long horizon here because, as we show below, extending the horizon further does not flatten the fitted line for the

[11] In the Internet Appendix III, we calibrate the long-run risk model of Bhamra, Kuehn, and Strebulaev (2010b) and show that long-run consumption risk is indeed an important driver of expected returns on corporate bonds in addition to credit spreads.

aggregate consumption growth. Even though using a long-run growth rate helps lower the slope, the fitted line is still much steeper than Panel A, which suggests that we need a higher risk-aversion coefficient to rationalize the observed variation in average returns if we use the aggregate consumption growth rate.

In Panel A, we use a shorter sample from 1984 to 2019 due to the availability of the CEX data, starting when the Treasury yield hit the post-war record high and ending when the yield is near zero. As a result, for most portfolios, the average returns in excess of T-bill rates are higher in Panel A than in Panel B, which starts from 1973. The implication of the unique sample period for the CEX data will be discussed in the next section.

3.2 Fit of the long-run risk model

3.2.1 Estimation using all test assets

In this section, we estimate the parameters of the long-run risk model in (12), and formally evaluate the performance of the model in explaining the cross-section of corporate bond premiums. Following Malloy, Moskowitz, and Vissing-Jørgensen (2009), we use the GMM framework to simultaneously estimate covariance between long-run consumption growth and asset returns together with model parameters.[12] For the test assets, we use 40 corporate bond portfolios sorted on 7 characteristics described in Table 2. Given the critique

[12] The GMM moment conditions are

$$E\begin{bmatrix} r_{i,t+1} - r_{f,t} + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} - \zeta - (\gamma-1)\varepsilon_{c,t\to t+S}\left(r_{i,t+1} - r_{f,t}\right) \\ \varepsilon_{c,t\to t+S} \end{bmatrix} = 0, \tag{14}$$

where $\varepsilon_{c,t\to t+S} = \sum_{s=0}^{S-1}\delta^s(c_{t+1+s} - c_{t+s}) - \mu_{\sum_{s=0}^{S-1}\delta^s(c_{t+1+s}-c_{t+s})}$, $\theta = \begin{pmatrix} \zeta & \gamma & \mu_{\sum_{s=0}^{S-1}\delta^s(c_{t+1+s}-c_{t+s})} \end{pmatrix}$ are the parameters to be estimated. Since there are 41 moment conditions in total and three free parameters, the GMM procedure finds the best parameters to minimize the sum of squared moments:

$$\min_{\theta} g_T(\theta)' W g_T(\theta) \tag{15}$$

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.

Effectively, we run cross-sectional regressions,

$$\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\hat{\sigma}^2(r_{i,t+1})}{2} - \frac{\hat{\sigma}^2(r_{f,t})}{2} = \zeta + (\gamma - 1)\hat{\sigma}_{i,c} + e_i, \tag{17}$$

$$\hat{\sigma}_{i,c} = c\hat{o}v\left(\sum_{s=0}^{S-1} \delta^s (c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}\right), \tag{18}$$

where $r_{i,t+1}$ is a 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 $\bar{R}^2 = 1 - \frac{Var_c(\hat{E}[R_i^e] - \widehat{R^e}_i)}{Var_c(\hat{E}[R_i^e])}$, where $\hat{E}[R_i^e] = \hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\hat{\sigma}^2(r_{i,t+1})}{2} - \frac{\hat{\sigma}^2(r_{f,t})}{2}$, and $\widehat{R^e}_i$ is the fitted value. To calculate the standard errors and 95% confidence intervals 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.[13]

Table 3 presents the main results of the article, including the estimated coefficients in (17) and cross-sectional $\bar{R}^2$ statistics with different values of S. In Panel A, the factors

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where $g_T(\theta)$ is the sample counterpart of the moments in (14), and W is the weighting matrix defined by,

$$W = \begin{pmatrix} I_{40} & 0 \\ 0 & H \end{pmatrix}, \tag{16}$$

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.

[13]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.

are based on CEX wealthy households' consumption, while in Panel B, they are from NIPA aggregate consumption. To evaluate the importance of long-run risk, we show the estimates in (17) with different values of S in the third to last columns in Panel A Table 3. Starting from the results using the consumption of wealthy households in CEX, we find that the risk-aversion estimates are lower at the medium horizon than for the short horizon. For example, when $S = 1$ quarter, γ is estimated at 24, and when $S = 20$ quarters, the estimate yields a reasonable level of risk aversion of $\gamma =$15. These results suggest that bond returns predict the wealthy households' consumption growth better over the medium term, which leads to a greater quantity of risk. As a result, the estimated risk aversion becomes lower as we increase S up to 20 quarters. When $S = 20$, the 95% bootstrapped confidence interval ranges from 7.1 to 25.9. Therefore, the risk-aversion coefficient is not statistically distinguishable from 10 – a commonly-used value in the long-run risk model (e.g. Bansal and Yaron (2004)) – but they are significantly different from zero, supporting the validity of the estimate.[14]

With regard to the explanatory power of the model, when $S = 1$ quarter, the cross-sectional $\bar{R}^2$ using wealthy households' consumption growth is 0.33. However, when $S =$ 20 quarters, the cross-sectional $\bar{R}^2$ increases to 0.80, which is substantial given that we use a one-factor model on 7 sets of portfolios, and higher than the value reported in Malloy,

[14]Although the estimated level of risk-aversion $\gamma =$15 is more reasonable than those provided in the literature (as summarized in Table IA2 in the Internet Appendix), it is still higher than the conventional level in an interval of 0.5 to 2. To achieve even lower values, we need additional features in the model. For example, Collin-Dufresne, Johannes, and Lochstoer (2016) show that an economy where an agent faces unknown model parameters and has to learn them using observed states generates high risk premiums for risky assets. Hansen and Miao (2022) extend the model of Hansen and Sargent (2011) where an agent is averse to model ambiguity and show that this additional uncertainty reduces investor demand for risky assets. These additional model features may help reduce the risk aversion in the paper even further. However, we do not take this path to emphasize the simplicity and transparency of the empirical analysis.

Moskowitz, and Vissing-Jørgensen (2009).[15] The cross-sectional $\bar{R}^2$ does not monotonically increase as S increases, owing to the relatively large measurement errors in the survey-based consumption growth rate. In Section 3.3, we address potential concerns arising from the noise in the data by confirming that similar results hold with $S = \infty$ using a VAR.

In contrast, if we estimate a model with NIPA aggregate consumption with $S = 1$ quarter, the estimated γ is 255, which is implausibly high but consistent with those found in the literature using contemporaneous aggregate consumption growth (e.g., 365 in Nagel and Singleton (2011)). Similar to the results using the CEX data, as S increases, the estimated risk-aversion parameter decreases up to a certain level of S. When $S = 2$ quarters, the estimated γ goes down to 131 and reaches the bottom when $S = 8$ and the estimated γ is 50. The cross-sectional $\bar{R}^2$ statistics remain similar, as it is 0.67 when $S = 1$ and 0.64 when $S = 8$, suggesting that the model using the NIPA aggregate consumption fits the data reasonably well, but not as good as wealthy households' consumption does.

The better performance for the wealthy households' consumption risk than the aggregate consumption partly reflects a variety of measurement issues for the aggregate data raised in the previous work (e.g., Aït-Sahalia, Parker, and Yogo (2004), Savov (2011), Kroencke (2017)). Furthermore, aggregate consumption may not capture well discretionary consumption-savings decisions that are tied to asset returns.[16] As a result, the consumption of wealthy households lines up better with observed asset returns than the aggregate consumption does.[17]

[15] Malloy, Moskowitz, and Vissing-Jørgensen (2009) report the cross-sectional $\bar{R}^2$ of 0.65 for the 25 size and book-to-market sorted portfolios using 24-quarter shareholder consumption growth, and 0.52 using 24-quarter top shareholder consumption growth (see their Table II).

[16] Furthermore, Kroencke (2017) points out that NIPA statisticians filter observable consumption, and this leads to seemingly too smoothed NIPA consumption measures.

[17] Kaplan and Violante (2014) show that some wealthy households behave as if they were constrained when

The intercept of the cross-sectional regression for wealthy households' 20-quarter consumption growth is 0.74% per quarter, suggesting that on average corporate bonds have returns that are too high during the sample period, while the intercept for the NIPA consumption growth is insignificant at 0.30%. This mispricing of the risk-free asset can be explained by the strong downward trend in Treasury yields over the sample period for the CEX data.

To account for the impact of falling Treasury yields, we repeat the exercise using corporate bond returns in excess of matched Treasury bonds with the same cash flows. To this end, we create synthetic Treasury securities with the same coupon and maturity as each corporate bond in the sample,[18] and use their returns as the risk-free rate of returns in (17). Since corporate and matching Treasury bonds have the same interest rate risk, this excess return is in principle not affected by shifts in the Treasury yield curve. Panel C of Table 3 reports the estimates for the Euler equation using CEX wealthy household consumption as a risk factor. We find that the estimated risk-aversion coefficient and the cross-sectional $\bar{R}^2$ remain nearly unchanged from our main results in Panel A. For example, for $S = 20$, risk aversion is estimated at 14 with $\bar{R}^2$ of 0.73. However, the intercept falls to -0.11%, which is statistically indistinguishable from zero. Therefore, once we account for changing Treasury yields, the wealthy households' consumption risk can price both corporate bond portfolios and risk-free assets simultaneously.

their assets are in illiquid assets such as real estate and retirement accounts. We argue that wealthy households in our setup are unlikely to be constrained as we measure assets using stocks, mutual funds, and bonds rather than real estate. Furthermore, we focus on the top 30% wealthy households to avoid constrained households.

[18]We use the fitted Treasury yield curve of Gurkaynak, Sack, and Wright (2006) available on the Federal Reserve's website and discount corporate bond cash flows using Treasury zero-coupon rates to obtain a price of matching Treasury bonds. Specifically, we use the parameter of the Svensson (1994) model available in the data set, and calculate the zero-coupon rate for the exact payment date for each coupon and principal for each corporate bond.

The better performance using wealthy households' consumption is not driven by the difference in data quality between NIPA and CEX. In Panel D of Table 3, we repeat the GMM estimation using CEX consumption using all households (rather than the top 30% asset holders). We find that when $S = 20$, the estimated risk-aversion coefficient is 64, higher than the estimate based on the NIPA aggregate consumption (50 with $S = 8$), while the cross-sectional $\bar{R}^2$ is 0.31. Thus, the success of the consumption-based model is not due to the usage of the CEX data per se. Rather, it is driven by the fact that we focus on wealthy households' consumption instead of aggregate consumption. In Internet Appendix Tables IA3 and IA4, we show that our results are not sensitive to the particular choice of the cutoff (30%) to define wealthy households.

The evidence above suggests that wealthy households' consumption prices the cross-section of corporate bonds well. These results are consistent with the model's performance on equity, as shown in Malloy, Moskowitz, and Vissing-Jørgensen (2009). To verify, in Table 4, we estimate the model using Fama-French 25 portfolios as test assets over the sample period up to 2019, extending the sample in the original study by 15 years.[19] With the quarterly consumption growth, the risk-aversion coefficients estimated from equities are 18 (CEX wealthy) and 166 (NIPA aggregate), lower than the corresponding values estimated from bonds (24 and 255). However, when we use 20-quarter wealthy households' consumption growth, the risk-aversion coefficient inferred from equity is 17, which is remarkably similar

[19] As in Malloy, Moskowitz, and Vissing-Jørgensen (2009), we exploit the entire time-series of returns starting from July 1926 to precisely estimate average returns. In order to obtain the bootstrap sample size that is equal to the number of real data observations for both the left-hand side (LHS) sample and the right-hand side (RHS) sample for this case, bootstrapping is performed in the following way. First, we place two sets of the data separately to be re-sampled: (1) time-period where only LHS is available and (2) time-period where both LHS and RHS are available. From each bootstrap sample, we attach the re-sampled first data set to the corresponding re-sampled second data set for each asset to obtain a bootstrap sample for the LHS. A bootstrap sample for the RHS is obtained directly from the re-sampled second data set.

to 15, the value estimated from corporate bonds. Thus, the corporate bond risk premiums appear too high relative to the equity counterpart if we use the short-term consumption growth as a risk factor. This tension, known as the credit spread puzzle, is often attributed to features specific to bond cash flows such as idiosyncratic tail risks (Culp, Nozawa, and Veronesi (2018)). We resolve the tension by showing that such risks are associated with the long-term consumption growth of wealthy households; once a left-tail event realizes, it disproportionately affects wealthy households' consumption in the future. Once we account for this link, we can build a one-factor model with a risk-aversion parameter that is consistent with both equity and bond risk premiums.

Though our focus is on wealthy households' consumption, we also attempt to estimate bondholders' consumption, motivated by the idea that the SDF is a function of the consumption of market participants. Due to the lack of data in CEX on whether households own bonds or not, we use a sample of the Survey of Consumer Finances which indicates bondholders and identify key characteristics that predict corporate bond ownership by estimating a Probit model. The details on the Probit analysis that links households' characteristics and bond ownership are provided in Internet Appendix IV. We then use the estimated coefficients to calculate the probability of bond ownership in the CEX sample, and create the consumption growth of households that have at least a 10% chance of holding corporate bonds. We call this series bondholders' consumption for short.

Panel E of Table 3 reports the GMM estimates using bondholders' consumption. We find that the results are fairly similar to our main results in Panel A. For example, when $S = 20$, the estimated risk-aversion coefficient is 14.9 with the cross-sectional $\bar{R}^2$ of 0.80.[20]

[20]For further robustness, in Internet Appendix V, we show that the results in Panel A are robust when we

3.2.2 Tests on the consistency of pricing performance across test assets

In this section, 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 is consistent across various asset classes. To examine the performance of the long-run risk model from this perspective, we separately estimate (17) using 7 sub-samples of portfolios sorted on credit rating, credit spreads, downside risk, idiosyncratic volatility, intermediary betas, long-term reversals, and maturity. Since each sub-sample has only 5 or 10 portfolios, the risk-aversion parameter will not be as precisely estimated as before. Thus, to evaluate the consistency of estimated γ, we also report the pricing performance in terms of $\bar{R}^2$ and $\frac{RMSE}{RMSR}$ for each portfolio group by imposing the same risk aversion estimated by all portfolios.

Panel A of Table 5 shows that risk-aversion estimates are consistent across assets for wealthy households' 20-quarter consumption growth. Once we estimate the Euler equation separately, the estimated γ is 17 for credit spread portfolios, 17 for downside risk portfolios, 35 for maturity portfolios, 14 for credit rating portfolios, 14 for intermediary beta portfolios, 15 for idiosyncratic volatility portfolios, and 13 for long-term reversal portfolios. Table 5 also compares $\bar{R}^2$ calculated with the risk aversion specific to each portfolio group with $\bar{R}^2$ with the risk aversion fixed at the value using all portfolios (i.e. $\gamma = 15$). These $\bar{R}^2$ are similar to each other, showing that allowing the risk-aversion parameter to vary across subsamples does not affect the fit of the model. The cross-sectional $\bar{R}^2$ for the intermediary beta portfolios is low at 0.24, but we will later show that the fit of the model improves

estimate the regression in (17) in reverse, switching the left-hand-side variable and right-hand-side variable.

significantly if we account for infinite-horizon consumption growth.

Figure 2 displays point estimates of risk aversion from each portfolio group and the one from all portfolio groups, as well as their 95% confidence intervals using the consumption of wealthy households. The two standard error bounds for these estimates include risk aversion of 15 from the main results in Table 3. Therefore, we cannot reject the hypothesis that the coefficient of risk aversion is equal to 15 for each portfolio group. This shows that although the measurement errors for sub-samples are large, the estimated risk aversion is consistent across different test assets.[21]

Figures 3 and 4 show the fit of the model graphically for CEX wealthy households' consumption and NIPA aggregate consumption, respectively. We plot the model-implied prediction for expected returns and the average excess returns in the data, using both full samples and 7 sub-samples of bond portfolios. In the figures, the observations lie close to the 45-degree line for most sub-portfolios. A notable exception is the fifth quintile of maturity and intermediary-beta-sorted portfolios which has higher average excess returns than the model's prediction. Because of these somewhat anomalous portfolios, the cross-sectional $\bar{R}^2$ using these sets of portfolios is lower than other portfolios. Still, overall results support the performance of the long-run risk model which generates consistent γ with similar magnitudes across different test assets using either wealthy households' consumption or aggregate consumption. Because risk-aversion estimates using wealthy households' consumption are more in line with theories, we focus on the consumption risk of wealthy households for the following analyses.

[21] In the Internet Appendix VI, we repeat the exercise using betas (rather than covariance) for the long-run consumption growth rate and show that the fit of the model and estimated price of risk are consistent with the main results.

3.3 More general models using a VAR

In the previous section, we use a 20-quarter consumption growth for a risk factor as an approximation to the long-run risk model which in principle depends on shocks to infinite-horizon consumption expectation. Though the performance of the approximate model is encouraging, we need to ensure that the results are not driven by the simplifying assumption. Thus, in this section, we estimate the conditional model in (11), which requires the estimates of the 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 (3) and (4). To save space, most of the estimation results are reported in the Internet Appendix VII.

To begin, we select a candidate set of state variables that predict consumption growth. To avoid an arbitrary choice of a few state variables, we rely on a large set of 160 macro and financial variables listed in Table IA5 in the Internet Appendix.[22] Then, we apply the principal component analysis as in Ludvigson and Ng (2007, 2009) and Roussanov (2014) and extract ten factors, $F_1, \ldots, F_{10}$. In total, we consider ten principal components with the maximum VAR lags of two as a candidate set of state variables. Next, based on these candidate variables, we find a subset that minimizes the Akaike Information Criterion (AIC) for consumption predictive regression in (3).

Panel A of Table 6 presents the estimated coefficients of VARs in (3) and (4). We find that the set of state variables we choose predicts consumption growth well. F_2, F_6, and F_8, and their one-month lags predict three months ahead of consumption growth with an

[22] 128 variables are from McCracken and Ng (2016).

adjusted R-squared of 0.027. 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.[23]

With this VAR estimate, we follow Hansen et al. (2007) and Hansen, Heaton, and Li (2008) and derive a more general form of the log stochastic discount factor for the long-run risk model with Epstein-Zin utility which accounts for the conditional expectation of consumption growth and does not assume EIS $= 1$. When EIS $\neq 1$, the factor is no longer a linear function of state variables and thus we need to log-linearize the function with approximation. Specifically, without constant terms and a contemporaneous consumption growth $(c_{t+1} - c_t)$ term that does not materially affect our result, the first-order expansion of the logarithm of the stochastic discount factor yields,

$$s_{t+1} \approx (1-\gamma)\lambda(\delta)w_{t+1} + \left(\frac{1}{\rho} - 1\right)\left(\frac{1}{2}w'_{t+1}\Theta_0 w_{t+1} + w'_{t+1}\Theta_1 x_t + \theta_1 x_t + \theta_2 w_{t+1}\right), \qquad (19)$$

where $\lambda(\delta)w_{t+1} = (E_{t+1} - E_t)\sum_{s=0}^{\infty}\delta^s(c_{t+1+s} - c_{t+s})$, and Θ_0, Θ_0, θ_1, θ_2 are functions of the parameters for the dynamics of state variables described in the Internet Appendix VII. The first term in (19) represents the log SDF when an EIS parameter $\rho = 1$, while the second term arises when EIS $\neq 1$. When EIS is one, the model does not require any restrictions on the shock structure to identify w_{t+1}. For this reason, we first focus our VAR analysis on the case for EIS $= 1$. We then conduct the analysis for the general case where EIS $\neq 1$ by identifying w_{t+1}.

[23]To support this claim, we show in Panel B of Table 6 that the selected factors generally do not exhibit the same predictive power for asset returns as for consumption growth. This implies that the quantity of risk using this VAR approach will not be mechanically led by a high predictive power of the selected factors for bond returns.

With the assumption of EIS $= 1$, we calculate shocks to the long-run expectation,

$$(E_{t+1} - E_t) \sum_{s=0}^{\infty} \delta^s (c_{t+1+s} - c_{t+s}) = \epsilon_{c,t+1} + \delta U_c (I - \delta G)^{-1} \epsilon_{x,t+1}, \tag{20}$$

where $\epsilon_{c,t+1} = \eta_0 w_{t+1}$ and $\epsilon_{x,t+1} = H w_{t+1}$. We use regression residuals of (3) and (4) for $\epsilon_{c,t+1}$ and $\epsilon_{x,t+1}$. The standard deviation of VAR-based shocks to long-run consumption is 8.19% per quarter, which is slightly lower than the standard deviation of unconditional 20-quarter consumption growth (8.82% per quarter).[24]

Armed with the estimated shocks to expectation for the long-run consumption growth in (20), we estimate the conditional model in (11) using GMM. Table 7 reports the estimates. Using all 40 portfolios as test assets, we find that the estimated risk-aversion parameter γ is 20. Although this point estimate is slightly higher than the estimate for the unconditional model of 15, a coefficient of 10 is well within two standard errors. The cross-sectional $\bar{R}^2$ is 0.83, even higher than 0.80 using the discounted 20-quarter consumption growth as a risk factor.

The analysis of 7 sub-samples also yields findings similar to our main results in Table 5. The risk-aversion estimates are consistent across portfolio groups with the two standard error bounds that include the full sample risk-aversion estimate of 20. Moreover, the cross-sectional $\bar{R}^2$ statistics are sizable, ranging from 0.64 to 0.99, except for maturity portfolios. Importantly, the model explains 90% of variations in average returns associated with intermediary factor betas.

Next, we allow EIS to be different from one and estimate the second term of the log SDF

[24] Table IA6 presents the summary statistics of shocks to the expectation for long-run consumption growth estimated using the VAR.

in (19). To this end, we impose a structure on the shock vector and estimate parameters in the second term. The Internet Appendix VII details terms in (19) and describes how we structurally identify the shock vector w_{t+1}. Table 8 presents the GMM cross-sectional test results with different values of EIS from 0.3 to 2.0. For an EIS of 1.5, which is used in Bansal and Yaron (2004), estimated γ is 21, very close to $\gamma = 20$ when EIS $= 1$, and the cross-sectional $\bar{R}^2$ of 0.84 is almost the same as the one with EIS $= 1$. The minimum and maximum estimated levels of risk aversion are 15 and 22 when EIS = 0.3 and EIS = 2, respectively. The two standard error bounds include risk-aversion levels around 10 for all values of EIS. Moreover, all risk-aversion estimates are statistically different from zero and the cross-sectional $\bar{R}^2$ statistics remain sizable regardless of the values of EIS. These results suggest that a key driver of the stochastic discount factor in (19) is its first term as used in our main exercise, and the second term which is added in this extension plays a minor role in explaining the cross-section of corporate bond risk premiums. The fact that the results are not sensitive to the choice of EIS justifies our initial assumption of the unitary EIS in the main results. In Internet Appendix VII, we extend the VAR to account for a volatility shock to the SDF as in Bansal et al. (2014) and confirm that the results are similar.

In sum, we find that either unconditional or conditional measures of the long-run risk explain the corporate bond risk premiums well.

4 Extension

4.1 Departure from the lognormality assumption

In deriving the Euler equation for log excess returns in (9), we assume that consumption growth and asset returns are jointly lognormally distributed. While this is a standard assumption in the literature, it 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 portfolio of risk-free assets and a short position on a put option on the underlying firm's asset, and thus their payoff is a nonlinear function of the asset value. This feature of corporate bonds' payoff may lead to the skewed distribution of bond returns, invalidating the Euler equation derived in (9).

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 up to the third order:

$$1 = E[S_{t+1}R_{i,t+1}], \tag{21}$$

$$\approx \bar{G}\left(1 + E[r_{i,t+1}] + \frac{1}{2}E[r_{i,t+1}^2] + (1-\gamma)E[\varepsilon_{c,t\to t+S}r_{i,t+1}] + \frac{1}{2}(1-\gamma)^2E[\varepsilon_{c,t\to t+S}^2 r_{i,t+1}] + \frac{1}{2}(1-\gamma)E[\varepsilon_{c,t\to t+S}r_{i,t+1}^2] + Const\right). \tag{22}$$

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 (22) shows that the risk premiums depend on covariance as well as coskewness.[25] Thus, we estimate the GMM using the moment

[25] The constant term in (22) 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 (23).

conditions:

$$0 = E\left[\begin{array}{c}\left(\begin{array}{c} r_{i,t+1} - r_{f,t} + \frac{E(r_{i,t+1}^2)}{2} - \frac{E(r_{f,t}^2)}{2} - \zeta - (\gamma-1)\varepsilon_{c,t\to t+S}\left(r_{i,t+1} - r_{f,t}\right) \\ +\frac{1}{2}(1-\gamma)^2\varepsilon_{c,t\to t+S}^2\left(r_{i,t+1} - r_{f,t}\right) - \frac{1}{2}(\gamma-1)\varepsilon_{c,t\to t+S}\left(r_{i,t+1}^2 - r_{f,t}^2\right)\end{array}\right) \\ \varepsilon_{c,t\to t+S}\end{array}\right]. \quad (23)$$

Unlike Harvey and Siddique (2000), the regression specification in (23) restricts the set of free parameters, (ζ, γ), to match those in the main analysis since the loadings on the covariance and coskewness both depend on the risk-aversion parameter γ.

Table 9 presents the estimated slope coefficients in (23) and the fit of the model using 40 bond portfolios as test assets. We find that the estimated γ is 8, much lower than γ of 15 from our main result. In terms of the cross-sectional fit, $\bar{R}^2$ is 0.38, also lower than the main result. Overall, we find evidence for the improvement of the level of risk aversion as we account for skewness in bond returns although the pricing performance is not as strong as before in this case.

4.2 International corporate bonds

As another extension, we perform an out-of-sample test using U.S. dollar-denominated corporate bonds issued by foreign firms. Specifically, we use bonds in the ICE Bank of America Merrill Lynch Global Corporate Index and High Yield Index. We focus on 30 economies with a non-trivial number of observations every year, including: Australia, Belgium, Brazil, Canada, Chile, China, Colombia, France, Germany, Hong Kong, India, Israel, Italy, Japan, Malaysia, Mexico, Netherlands, Norway, Peru, Qatar, Russia, Singapore, South Korea, Spain, Sweden, Switzerland, Thailand, Turkey, the United Arab Emirates, and the United Kingdom. We use U.S. dollar-denominated bonds because according to Maggiori, Neiman, and Schreger (2020), there is a home currency bias for bond investors, and thus those bonds are likely to be included in the U.S. investors' portfolios. Using those bonds, we form 40 portfolios based on the 7 characteristics as in the main results. We then estimate the Euler equation in (17) and report the estimated risk-aversion coefficients in Table 10.

Using the international corporate bond portfolios, the estimated risk-aversion coefficient is 11 for the 20-quarter consumption growth of wealthy households, which is close to the estimate of 15 in the main results. Since the model generates a reasonable cross-sectional R-squared of 0.46, long-run consumption risk explains these international bonds with a parameter similar to the main results for the U.S. corporate bonds.

4.3 Time-series analysis using factor-mimicking portfolios and comparison with other factor models

In this section, we compare the performance of our consumption risk factor with that of other risk factors proposed in the literature. To this end, we follow the econometric framework of Barillas and Shanken (2018) and regress a risk factor on other factors to study whether it carries risk premiums unexplained by the other factors. Since this approach requires the factor to be an excess return, we create a factor-mimicking portfolio for the wealthy households' long-run consumption risk. To construct the mimicking portfolio, we project the discounted 20-quarter cumulative consumption growth (unconditional measure) or shocks to the long-run expectation (conditional measure) on quarterly excess returns of six bond portfolios independently sorted on 3 maturity bins and 2 credit rating bins (investment-grade and high-yield),

$$\text{(Long-run consumption shock)}_{t+1} = a + b' R_{t+1} + u_{t+1}, \tag{24}$$

where (Long-run consumption shock)$_{t+1} = \sum_{s=0}^{19} \delta^s (c_{t+1+s} - c_{t+s})$ or $(\hat{E}_{t+1} - \hat{E}_t) \sum_{s=0}^{\infty} \delta^s (c_{t+1+s} - c_{t+s})$. A factor-mimicking portfolio is given by the fitted value of this projection $\hat{b}' R_{t+1}$. To extend the sample period, we estimate b using the sample after March 1984 and assume that the same b applies to the earlier sample from April 1973, resulting in the sample extended by roughly 10 years. We find that the average excess return on the factor mimicking portfolio is 0.68% and 0.51% per quarter for the unconditional and conditional measures, respectively.

For comparison, we gather 10 asset pricing factors proposed in the literature: the value, size, profitability, investment, term, and default factors of Fama and French (1993, 2015); the intermediary capital factor of He, Kelly, and Manela (2017); the bond market, downside risk, and credit risk factors of Bai, Bali, and Wen (2019). Since the intermediary capital factor is not an excess return, we project it on the same base assets as we did for the consumption risk factor using (24) and create an intermediary factor-mimicking portfolio.

Panel A1 of Table 11 reports the average excess returns on the other factors and the estimates for the regression of these factors on the consumption-mimicking portfolio returns. We find that, except for the size and default factors, the factors proposed in the literature earn significantly positive risk premiums during our sample period.

The intercept of the regressions measures the risk premiums on these factors unexplained by the consumption-mimicking portfolio. The estimates in Panel A1 suggest that the bond risk factors have alphas lower than the average excess returns. For example, the bond market, downside risk, credit risk, and the intermediary risk factors have alphas of -0.08%, -0.12%, -0.06%, and -0.39% respectively, and these estimates are insignificantly different from zero. In contrast, we find that the equity risk factors are largely orthogonal to the consumption-mimicking portfolio with near-zero R-squared. As a result, the estimated alphas are similar to the average excess returns. These results are expected because the consumption-mimicking portfolio is created by a projection on bond returns.

In Panel A2, we repeat the exercise using the mimicking portfolios for the VAR-based long-run consumption shocks. This alternative mimicking portfolio generates higher betas for the other bond factors, lowering their alphas even further. Overall, we find that the long-run consumption factor explains other bond factors well.

Next, we switch the left-hand side and right-hand side of the regression and regress the consumption mimicking portfolios on each of the other risk factors. Panels B1 and B2 of Table 11 report the estimated intercepts, slope coefficients, and adjusted R-squared values of the regression.

We find that the alphas of the consumption-mimicking portfolio are positive for all regression specifications. When it is regressed on other bond factors, the alpha is lower than the average excess returns but remains significantly positive. For example, the alpha of the consumption-mimicking portfolio against the bond market, downside risk, credit risk, and the intermediary factors is 0.36%, 0.51%, 0.58%, and 0.35%, respectively. When regressed on the stock factors, the alphas are virtually the same as the average excess returns of 0.68%. The results using the VAR-based consumption risk, reported in Panel B2, are highly similar to the one using the 20-quarter consumption growth. These results show that the consumption risk factor is not subsumed by other bond and equity risk factors. Furthermore, it carries information on corporate bond risk premiums that explain the existing bond factors.

4.4 Illiquidity of corporate bonds

Bai, Bali, and Wen (2019) show that illiquidity measures predict the cross-section of corporate bond returns. To examine whether the 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 the 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. For the noise betas, we compute 36-month rolling betas using the first difference in the noise measure.

We estimate the GMM cross-sectional regressions using 20 illiquidity-sorted portfolios with the CEX wealthy household consumption and NIPA aggregate consumption. In Table 12, with the CEX consumption of wealthy households, the risk-aversion estimate is statistically indistinguishable from zero. A poor performance of the model in explaining illiquidity-sorted portfolios is exacerbated with the NIPA aggregate consumption, as the estimated γ is negative at -27 in this case. 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.

5 Conclusion

In this article, we show that a one-factor model based on long-run consumption risk can explain the cross-section of corporate bond returns. Consistent with the literature on equity risk premiums, we find that our model explains the most cross-sectional variation in risk premiums associated with credit spreads, maturity, credit rating, downside risk, idiosyncratic volatility, the intermediary factor betas, and long-term reversals with a reasonable risk-aversion coefficient of 15. The performance of the one-factor model suggests that it is possible for a single macroeconomic factor to summarize the various dimensions of corporate bond risk premiums previously described by multi-factor models in the literature.

Our finding resonates 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 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 poorly estimated historical default frequency.

Our results also point to the re-interpretation of the well-known class of factor models based on shocks to the financial intermediary's capital (e.g. Adrian, Etula, and Muir (2014), He, Kelly, and Manela (2017)). The fact that consumption shocks generate a pattern in covariance that matches average returns is striking given that corporate bonds are mainly owned by financial institutions and traded in dealer-driven over-the-counter market. However, our findings are not mutually exclusive with the financial intermediary-based explanation of risk premiums. It is possible to argue that depleted intermediary capital causes wealthy households' expectations for the long-run consumption growth to fall, or vice versa. As pointed out by Santos and Veronesi (2021), the fact that the long-run consumption risk correlates with the prediction of the intermediary-based model does not indicate which shock causes the other. To ascertain 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. **Summary Statistics of Wealthy Households' and Aggregate Consumption Growth: Volatility and Sensitivity with Respect to Asset Returns**

This table reports volatility of S-quarter growth rate of CEX wealthy households' consumption, CEX aggregate consumption, or NIPA aggregate consumption in Panel A and time-series regressions of those consumption measures on aggregate bond returns over different long-run horizons S in Panel B,

$$\sum_{s=0}^{S-1} \delta^s (c_{t+1+s} - c_{t+s}) = b_0 + b_1 r_{t+1} + u_{t,t+1+S},$$

where $\delta = 0.95^{1/4}$. Aggregate corporate bond returns are the value-weighted average bond returns using the bond-level data used in this study. Time period spans from April 1973 to December 2019 for NIPA data and March 1984 to December 2019 for CEX data. Standard errors based on Newey and West (1987) are reported in parentheses.

$S =$	1	2	4	8	12	16	20	24
Panel A: Volatility of consumption growth								
CEX wealthy	0.083	0.088	0.086	0.089	0.089	0.088	0.088	0.084
CEX aggregate	0.024	0.025	0.023	0.021	0.024	0.022	0.023	0.022
NIPA aggregate	0.004	0.008	0.013	0.021	0.027	0.031	0.035	0.038
Panel B: Sensitivity to corporate bond returns								
CEX wealthy	0.260	0.370	0.253	0.098	0.145	0.450	0.383	0.258
(s.e.)	(0.130)	(0.126)	(0.173)	(0.108)	(0.132)	(0.129)	(0.114)	(0.116)
R^2	0.008	0.015	0.007	0.001	0.002	0.023	0.016	0.008
CEX aggregate	0.149	0.052	0.089	-0.012	0.027	0.044	0.037	0.037
(s.e.)	(0.044)	(0.061)	(0.054)	(0.076)	(0.057)	(0.060)	(0.074)	(0.063)
R^2	0.039	0.004	0.013	0.000	0.001	0.004	0.002	0.003
NIPA aggregate	-0.004	0.021	0.068	0.113	0.142	0.142	0.129	0.112
(s.e.)	(0.011)	(0.018)	(0.028)	(0.034)	(0.041)	(0.052)	(0.059)	(0.066)
R^2	0.001	0.012	0.042	0.042	0.041	0.031	0.021	0.014

Table 2. **Average Excess Returns and Short-Run/Long-Run Covariances Between Excess Returns and Wealthy Households' Consumption Growth**

This table reports average excess returns, $\hat{E}(r_{i,t+1}-r_{f,t})+\frac{\hat{\sigma}^2(r_{i,t+1})}{2}-\frac{\hat{\sigma}^2(r_{f,t})}{2}$ and the quantity of risk for the short-run risk (denoted by SR): $\hat{cov}(c_{t+1}-c_t, r_{i,t+1}-r_{f,t})$ and the long-run risk (denoted by LR): $\hat{cov}(\sum_{s=0}^{19}\delta^s(c_{t+1+s}-c_{t+s}), r_{i,t+1}-r_t^f)$ for each portfolio group where $r_{i,t+1}$ is the quarterly log return of an asset i, $r_{f,t}$ is the quarterly log rate of 30-day T-bill, $\delta = 0.95^{1/4}$, c_t is the log consumption. The long-run consumption risk factor is measured by the discounted cumulative 20-quarter consumption growth. Consumption of wealthy households defined as the top 30% of asset holders from CEX data is used. 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 March 1984 to December 2019.

	Low 1	2	3	4	5	6	7	8	9	High 10	High - Low 10 - 1
Panel A: Credit spread portfolios											
Returns (%)	0.8219	0.9969	1.0989	1.0845	1.1634	1.2405	1.2518	1.3210	1.3151	2.4959	1.6740
	(0.1104)	(0.1191)	(0.1529)	(0.168)	(0.1834)	(0.1688)	(0.1916)	(0.1883)	(0.2475)	(0.4835)	(0.4688)
SR (%)	0.0091	0.0217	0.0199	0.0261	0.0327	0.0322	0.0263	0.0278	0.0149	0.0504	0.0413
	(0.0047)	(0.0085)	(0.0105)	(0.0092)	(0.0091)	(0.009)	(0.01)	(0.0088)	(0.0113)	(0.0173)	(0.0188)
LR (%)	0.0186	0.0219	0.0197	0.0226	0.0258	0.0226	0.0232	0.0296	0.0399	0.1115	0.0929
	(0.0063)	(0.0075)	(0.0091)	(0.0082)	(0.0088)	(0.0077)	(0.0074)	(0.0076)	(0.0146)	(0.0368)	(0.0379)

	Low 1	2	3	4	High 5	High - Low 5 - 1	Low 1	2	3	4	High 5	High - Low 5 - 1
Panel B: Downside portfolios							Panel C: Maturity portfolios					
Returns (%)	0.7512	1.0641	1.1965	1.3227	1.9685	1.2173	0.8750	1.1297	1.2188	1.3261	1.5266	0.6516
	(0.0531)	(0.1282)	(0.1872)	(0.2378)	(0.3919)	(0.3580)	(0.0683)	(0.1334)	(0.2083)	(0.1960)	(0.2410)	(0.2008)
SR (%)	0.0115	0.0250	0.0368	0.0407	0.0572	0.0457	0.0122	0.0196	0.0233	0.0286	0.0387	0.0265
	(0.0043)	(0.0075)	(0.0104)	(0.0118)	(0.0147)	(0.0125)	(0.0037)	(0.0062)	(0.0090)	(0.0126)	(0.0145)	(0.0118)
LR (%)	0.0147	0.0266	0.0300	0.0363	0.0855	0.0709	0.0211	0.0294	0.0352	0.0300	0.0323	0.0112
	(0.0046)	(0.0059)	(0.0084)	(0.0092)	(0.0232)	(0.0231)	(0.0048)	(0.0071)	(0.0105)	(0.0084)	(0.0116)	(0.0076)
Panel D: Rating portfolios							Panel E: Intermediary portfolios					
Returns (%)	1.0844	1.1498	1.1757	1.2472	1.6225	0.5381	0.9271	1.0075	1.0647	1.1280	1.5068	0.5797
	(0.1177)	(0.1959)	(0.1619)	(0.1852)	(0.3221)	(0.2677)	(0.2751)	(0.1038)	(0.1103)	(0.1354)	(0.3014)	(0.2505)
SR (%)	0.0223	0.0275	0.0270	0.0275	0.0227	0.0004	0.0212	0.0205	0.0196	0.0238	0.0162	-0.0050
	(0.0098)	(0.0099)	(0.0102)	(0.0088)	(0.0141)	(0.0102)	(0.0081)	(0.0069)	(0.0079)	(0.0077)	(0.0149)	(0.0089)
LR (%)	0.0192	0.0233	0.0259	0.0374	0.0579	0.0387	0.0422	0.0298	0.0257	0.0325	0.0456	0.0034
	(0.0077)	(0.0079)	(0.0104)	(0.0082)	(0.0211)	(0.0199)	(0.0112)	(0.0078)	(0.0069)	(0.0066)	(0.0176)	(0.0092)
Panel F: Idiosyncratic portfolios							Panel G: Long-term reversal portfolios					
Returns (%)	0.7479	1.0495	1.3109	1.4016	1.8245	1.0767	1.1421	1.0146	1.2065	1.0361	2.0200	0.8779
	(0.0530)	(0.1392)	(0.1861)	(0.2480)	(0.3492)	(0.3215)	(0.2137)	(0.1526)	(0.1174)	(0.2170)	(0.3402)	(0.3332)
SR (%)	0.0107	0.0264	0.0352	0.0397	0.0638	0.0531	0.0156	0.0359	0.0262	0.0326	0.0394	0.0238
	(0.0041)	(0.0075)	(0.0104)	(0.0119)	(0.0158)	(0.0147)	(0.0118)	(0.0088)	(0.0093)	(0.0086)	(0.0095)	(0.0102)
LR (%)	0.0150	0.0259	0.0330	0.0371	0.0842	0.0692	0.0114	0.0353	0.0219	0.0438	0.0872	0.0759
	(0.0044)	(0.0060)	(0.0075)	(0.0097)	(0.0209)	(0.0215)	(0.0103)	(0.0085)	(0.0096)	(0.0085)	(0.0188)	(0.0195)

Table 3. **GMM Cross-Sectional Regression Using All Corporate Bond Portfolios**

This table reports GMM cross-sectional regression results over different long-run horizons S: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\hat{\sigma}^2(r_{i,t+1})}{2} - \frac{\hat{\sigma}^2(r_{f,t})}{2} = \zeta + (\gamma - 1)\hat{cov}(\sum_{s=0}^{S-1} \delta^s(c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) + e_i$ where $r_{i,t+1}$ is the quarterly log return of an asset i, $r_{f,t}$ is the quarterly log rate of 30-day T-bill in Panels A, B, D and E while it is the log return on matching Treasury bonds in Panel C, $\delta = 0.95^{1/4}$, c_t is the log consumption. The long-run consumption risk factor is measured by the discounted cumulative consumption growth over multiple horizons $\sum_{s=0}^{S-1} \delta^s(c_{t+1+s} - c_{t+s})$. Panels A, C and E report the results using wealthy households (defined as the top 30% of asset holders) from CEX, while Panels B and D report those using the consumption growth of aggregate households from NIPA and from CEX, respectively. Panel E report the results using the consumption of CEX corporate bondholders. The quantity of risk is jointly estimated with parameters ζ, η, and γ using GMM. Test assets are 40 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 5 long-term reversal 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 March 1984 to December 2019 for CEX and from February 1973 to December 2019 for NIPA. Unconditional pricing errors ζ and η are multiplied by 100 for ease of exposition.

S (quarters)	1	2	4	8	12	16	20	24
Regressions: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\hat{\sigma}^2(r_{i,t+1})}{2} - \frac{\hat{\sigma}^2(r_{f,t})}{2} = \zeta + (\gamma - 1)\hat{cov}(\sum_{s=0}^{S-1} \delta^s(c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) + e_i$								
Panel A: CEX consumption of wealthy households								
ζ (%)	0.71	0.46	0.85	0.99	0.96	0.55	0.74	0.73
	[0.46 1.29]	[0.12 1.20]	[0.43 1.23]	[0.60 1.41]	[0.50 1.69]	[0.24 0.93]	[0.42 0.96]	[0.24 1.10]
γ	23.5	23.6	17.1	21.9	16.8	16.1	15.4	23.5
	[-2.3 40.7]	[0.5 35.1]	[-4.7 31.6]	[-20.0 45.7]	[-20.5 39.1]	[4.3 25.9]	[7.1 25.9]	[5.8 46.5]
$\bar{R}^2$	0.33	0.72	0.21	0.29	0.13	0.69	0.80	0.62
	[0.00 0.67]	[0.00 0.93]	[0.00 0.75]	[0.00 0.66]	[0.00 0.55]	[0.05 0.90]	[0.26 0.90]	[0.08 0.80]
$\frac{RMSE}{RMSR}$	0.22	0.14	0.25	0.24	0.26	0.14	0.12	0.17
Number of assets	40	40	40	40	40	40	40	40
Number of asset-month	16,940	16,820	16,580	16,100	15,620	15,140	14,660	14,180
Panel B: NIPA aggregate consumption								
ζ (%)	0.63	0.33	0.29	0.26	0.18	0.24	0.30	0.78
	[0.23 1.00]	[-0.06 1.01]	[-0.06 1.02]	[-0.17 1.01]	[-0.17 0.97]	[-0.14 1.10]	[-0.07 1.18]	[0.19 1.29]
γ	254.6	130.7	71.0	50.1	50.4	56.8	78.1	29.6
	[119.4 332.5]	[35.9 188.6]	[17.5 101.8]	[17.1 67.9]	[12.8 69.9]	[-24.3 74.8]	[-56.0 92.3]	[-71.0 83.5]
$\bar{R}^2$	0.67	0.57	0.59	0.64	0.62	0.58	0.53	0.04
	[0.30 0.78]	[0.08 0.74]	[0.05 0.76]	[0.09 0.79]	[0.08 0.82]	[0.05 0.81]	[0.00 0.82]	[0.00 0.76]
$\frac{RMSE}{RMSR}$	0.18	0.21	0.21	0.20	0.20	0.19	0.22	0.32
Number of assets	40	40	40	40	40	40	40	40
Number of asset-month	21,400	21,280	21,040	20,560	20,080	19,600	19,120	18,640

Table 3. GMM Cross-Sectional Regression Using All Corporate Bond Portfolios (Cont'd)

S (quarters)	1	2	4	8	12	16	20	24
Regressions: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\hat{\sigma}^2(r_{i,t+1})}{2} - \frac{\hat{\sigma}^2(r_{f,t})}{2} = \zeta + (\gamma - 1)\hat{cov}(\sum_{s=0}^{S-1} \delta^s (c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) + e_i$								
Panel C: CEX consumption of wealthy households using matching treasuries as risk-free assets								
ζ (%)	0.31	-0.11	0.08	0.02	0.17	-0.12	-0.11	-0.01
	[-0.12 0.53]	[-0.28 0.25]	[-0.27 0.29]	[-0.22 0.33]	[-0.15 0.39]	[-0.32 0.16]	[-0.28 0.12]	[-0.23 0.31]
γ	17.1	19.1	11.4	23.3	12.2	12.4	14.0	21.9
	[-24.7 45.8]	[-17.6 32.1]	[-11.0 33.1]	[-21.1 49.8]	[-29.1 37.6]	[0.1 23.3]	[5.6 21.4]	[0.7 47.4]
$\bar{R}^2$	0.09	0.43	0.09	0.35	0.07	0.41	0.73	0.54
	[0.00 0.55]	[0.00 0.75]	[0.00 0.65]	[0.00 0.76]	[0.00 0.55]	[0.00 0.75]	[0.11 0.85]	[0.01 0.81]
$\frac{RMSE}{RMSR}$	0.77	0.62	0.79	0.66	0.82	0.70	0.46	0.58
Number of assets	40	40	40	40	40	40	40	40
Number of asset-month	16,940	16,820	16,580	16,100	15,620	15,140	14,660	14,180
Panel D: CEX aggregate consumption								
ζ (%)	0.44	0.79	0.44	1.02	0.52	0.43	0.83	0.92
	[0.26 1.22]	[0.51 1.32]	[0.21 1.22]	[0.64 1.41]	[0.27 1.27]	[0.23 1.39]	[0.33 1.36]	[0.11 1.49]
γ	60.7	85.6	75.8	71.2	104.7	108.4	64.4	51.3
	[-23.6 82.1]	[-53.6 102.4]	[-25.7 103.3]	[-43.3 95.3]	[-41.4 118.9]	[-56.4 118.8]	[-40.7 90.3]	[-65.6 119.7]
$\bar{R}^2$	0.61	0.66	0.48	0.70	0.79	0.50	0.31	0.08
	[0.00 0.89]	[0.01 0.83]	[0.00 0.89]	[0.00 0.85]	[0.01 0.92]	[0.00 0.88]	[0.00 0.88]	[0.00 0.91]
$\frac{RMSE}{RMSR}$	0.17	0.16	0.20	0.15	0.13	0.18	0.22	0.27
Number of assets	40	40	40	40	40	40	40	40
Number of asset-month	16,940	16,820	16,580	16,100	15,620	15,140	14,660	14,180
Panel E: CEX consumption of bondholders								
ζ (%)	0.85	0.64	0.52	0.98	0.80	0.50	0.82	0.68
	[0.68 1.36]	[0.47 1.14]	[0.31 1.13]	[0.73 1.34]	[0.44 1.47]	[0.3 1.03]	[0.44 1.16]	[0.41 1.29]
γ	26.3	20.7	21.6	23.9	28.9	19.6	14.9	22.0
	[1.6 38.9]	[3.3 30.2]	[-0.5 27.7]	[-19.3 34.2]	[-15.4 41.8]	[1.2 28.7]	[6.6 24.1]	[1.7 28.7]
$\bar{R}^2$	0.44	0.86	0.69	0.67	0.56	0.79	0.80	0.68
	[0.01 0.66]	[0.01 0.93]	[0.00 0.90]	[0.00 0.83]	[0.00 0.84]	[0.01 0.90]	[0.15 0.91]	[0.02 0.85]
$\frac{RMSE}{RMSR}$	0.20	0.10	0.15	0.16	0.18	0.11	0.12	0.16
Number of assets	40	40	40	40	40	40	40	40
Number of asset-month	16,940	16,820	16,580	16,100	15,620	15,140	14,660	14,180

Table 4. **GMM Cross-Sectional Regression Using Equities**

This table reports GMM cross-sectional regression results with different long-run horizons S using equity portfolios as test assets: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} = \zeta + (\gamma - 1)\hat{cov}(\sum_{s=0}^{S-1} \delta^s (c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) + e_i$ where $r_{i,t+1}$ is the quarterly log return of an asset i, $r_{f,t}$ is the log rate of 30-day T-bill, $\delta = 0.95^{1/4}$, c_t is the log consumption. The long-run consumption risk factor is measured by the discounted cumulative consumption growth over multiple horizons $\sum_{s=0}^{S-1} \delta^s (c_{t+1+s} - c_{t+s})$. The quantity of risk is jointly estimated with parameters ζ and γ using GMM. Test assets are 25 Fama-French size and book-to-market sorted portfolios from July 1926 to December 2019. 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 March 1984 to December 2019 for CEX wealthy households' consumption and from April 1959 to December 2019 for NIPA aggregate consumption. Unconditional pricing errors ζ are multiplied by 100 for ease of exposition.

S (quarters) =	1	2	4	8	12	16	20	24
Panel A: CEX consumption of wealthy households								
ζ (%)	2.59	1.60	2.23	2.30	2.72	2.14	1.69	2.50
	[1.46 3.56]	[0.60 3.29]	[1.32 3.28]	[1.45 3.40]	[1.79 3.50]	[1.34 3.58]	[0.84 3.15]	[1.71 3.64]
γ	18.0	16.8	13.3	20.5	11.2	10.7	17.3	20.6
	[-15.3 26.8]	[-6.4 24.5]	[0.7 25.7]	[1.2 25.5]	[-6.7 23.6]	[-8.0 19.2]	[2.1 24.5]	[-14.6 25.8]
$\bar{R}^2$	0.27	0.35	0.22	0.55	0.10	0.10	0.43	0.31
	[0.00 0.48]	[0.00 0.49]	[0.00 0.46]	[0.01 0.68]	[0.00 0.56]	[0.00 0.45]	[0.00 0.58]	[0.00 0.60]
$\frac{RMSE}{RMSR}$	0.18	0.17	0.19	0.15	0.20	0.20	0.16	0.18
Number of assets	25	25	25	25	25	25	25	25
Number of asset-month	10,750	10,675	10,525	10,225	9,925	9,625	9,325	9,025
Panel B: NIPA Aggregate consumption								
ζ (%)	0.05	0.39	1.91	0.93	1.48	1.86	1.68	1.75
	[-0.99 3.80]	[-1.07 3.99]	[0.02 3.63]	[0.01 3.06]	[0.11 2.67]	[0.69 2.78]	[0.70 2.79]	[0.99 2.91]
γ	165.7	105.4	30.4	46.4	37.5	31.5	29.3	28.3
	[-129.1 242.4]	[-82.7 171.0]	[-38.6 98.6]	[-9.8 80.5]	[7.4 81.2]	[6.8 85.8]	[3.7 74.4]	[0.6 61.8]
$\bar{R}^2$	0.50	0.31	0.07	0.40	0.43	0.34	0.34	0.31
	[0.05 0.69]	[0.00 0.62]	[0.00 0.55]	[0.00 0.72]	[0.04 0.72]	[0.03 0.69]	[0.01 0.67]	[0.01 0.61]
$\frac{RMSE}{RMSR}$	0.15	0.18	0.21	0.17	0.16	0.17	0.18	0.18
Number of assets	25	25	25	25	25	25	25	25
Number of asset-month	18,225	18,150	18,000	17,700	17,400	17,100	16,800	16,500

Table 5. **GMM Cross-Sectional Regression for Each Portfolio Group**

This table reports GMM cross-sectional regression results for each portfolio group: $\hat{E}[r_{i,t+1}-r_{f,t}]+\frac{\hat{\sigma}^2(r_{i,t+1})}{2}-\frac{\hat{\sigma}^2(r_{f,t})}{2}=\zeta+(\gamma-1)\hat{cov}(\sum_{s=0}^{S-1}\delta^s(c_{t+1+s}-c_{t+s}),r_{i,t+1}-r_{f,t})+e_i$ where $r_{i,t+1}$ is the quarterly log return of an asset i, $r_{f,t}$ is the quarterly log rate of 30-day T-bill, $\delta=0.95^{1/4}$, c_t is the log consumption. The long-run consumption risk factor is measured by the discounted cumulative consumption growth over multiple horizons $\sum_{s=0}^{S-1}\delta^s(c_{t+1+s}-c_{t+s})$ where $S=20$ quarters for CEX wealthy household consumption (Panel A) and $S=8$ quarters for NIPA aggregate consumption (Panel B). The quantity of risk is jointly estimated with parameters ζ, η, and γ using GMM. Test assets are 40 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 5 long-term reversal 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 $RMSR=\sqrt{\frac{1}{N}\sum_{i=1}^{N}E(R_i^e)^2}$. '$\bar{R}^2$ with same γ' and '$\frac{RMSE}{RMSR}$ with same γ' report the pricing performance by imposing γ estimated using all portfolios. Time period spans from March 1984 to December 2019 for CEX and from February 1973 to December 2019 for NIPA. 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	Reversal portfolios	All portfolios
Panel A: CEX consumption of wealthy households								
ζ (%)	0.75	0.64	0.20	0.82	0.67	0.71	0.81	0.74
	[0.33 1.00]	[-0.01 0.85]	[-0.46 1.28]	[0.13 1.17]	[0.25 1.56]	[0.10 0.94]	[0.47 1.13]	[0.42 0.96]
γ	16.7	17.1	35.3	14.4	14.1	15.1	12.8	15.4
	[8.7 32.3]	[6.6 42.6]	[-14.9 68.6]	[-2.0 39.0]	[-19.3 27.6]	[5.2 40.7]	[6.6 19.5]	[7.1 25.9]
$\bar{R}^2$	0.94	0.96	0.56	0.96	0.24	0.87	0.69	0.80
	[0.36 0.98]	[0.68 1.00]	[0.01 0.96]	[0.06 0.99]	[0.00 0.87]	[0.45 0.99]	[0.30 0.94]	[0.26 0.90]
$\bar{R}^2$ with same γ	0.93	0.95	0.37	0.96	0.24	0.87	0.66	0.80
$\frac{RMSE}{RMSR}$	0.08	0.06	0.12	0.03	0.15	0.10	0.16	0.12
$\frac{RMSE}{RMSR}$ with same γ	0.09	0.07	0.14	0.05	0.18	0.10	0.17	0.12
Number of assets	10	5	5	5	5	5	5	40
Number of asset-month	3,690	1,845	1,845	1,845	1,785	1,845	1,805	14,660
Panel B: NIPA aggregate consumption								
ζ (%)	0.17	0.02	0.53	0.23	0.18	0.16	0.08	0.26
	[-1.24 0.98]	[-0.75 0.97]	[0.33 1.13]	[-1.50 1.04]	[-0.43 1.14]	[-0.32 1.00]	[-0.77 1.29]	[-0.17 1.01]
γ	59.3	72.0	22.6	41.5	47.8	63.4	88.9	50.1
	[31.4 113.5]	[29.2 149.2]	[-11.8 46.4]	[17.1 98.8]	[-24.5 108.3]	[23.6 123.8]	[-35.2 141.9]	[17.1 67.9]
$\bar{R}^2$	0.86	0.97	0.43	0.96	0.98	0.98	0.46	0.64
	[0.53 0.94]	[0.49 1.00]	[0.00 0.73]	[0.73 0.98]	[0.01 0.98]	[0.43 0.99]	[0.00 0.86]	[0.09 0.79]
$\bar{R}^2$ with same γ	0.84	0.89	-0.27	0.91	0.98	0.94	0.35	0.64
$\frac{RMSE}{RMSR}$	0.15	0.05	0.10	0.05	0.03	0.04	0.22	0.20
$\frac{RMSE}{RMSR}$ with same γ	0.17	0.13	0.23	0.20	0.15	0.10	0.33	0.20
Number of assets	10	5	5	5	5	5	5	40
Number of asset-month	5,300	2,540	2,660	2,660	2,480	2,540	2,380	20,560

Table 6. **VAR Estimation**

Panel A reports the VAR estimation with the consumption growth and the selected state variables. 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 160 pre-selected variables. Panel B reports the predictive OLS regression of quarterly returns to the credit spread sorted decile portfolios on the selected state variables. $S1$ and $S10$ denotes the lowest and highest credit spread portfolio, respectively. 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. Time period spans from March 1984 to December 2019. t denotes a month t.

	x_{t-2}						Constant	Adj.R^2	N
Dep. Var.	$F_{2,t-2}$	$F_{6,t-2}$	$F_{8,t-2}$	$F_{2,t-3}$	$F_{6,t-3}$	$F_{8,t-3}$			
Panel A: VAR estimation									
$c_{t+1} - c_{t-2}$	-0.0020	0.0484	0.1379	-0.0294	0.0280	-0.0960	-0.0088	0.0275	430
	(0.0158)	(0.0247)	(0.0398)	(0.0151)	(0.0251)	(0.0394)	(0.0047)		
$F_{2,t+1}$	0.0197	0.0511	-0.1162	0.0213	-0.0231	0.1120		-0.0200	430
	(0.0568)	(0.0821)	(0.1251)	(0.0751)	(0.068)	(0.1399)			
$F_{6,t+1}$	0.0333	0.1344	-0.0148	0.0225	0.0879	0.0698		0.0141	430
	(0.029)	(0.0501)	(0.0863)	(0.0318)	(0.0600)	(0.0813)			
$F_{8,t+1}$	0.0096	0.0123	0.4828	-0.0105	0.0359	0.3239		0.2941	430
	(0.0203)	(0.0259)	(0.0439)	(0.0174)	(0.0298)	(0.0434)			
$F_{2,t}$	0.0076	0.1205	0.0942	0.0183	0.0313	-0.1017		-0.0154	430
	(0.0538)	(0.1112)	(0.2185)	(0.0786)	(0.0767)	(0.2003)			
$F_{6,t}$	-0.0536	0.1512	-0.0613	0.0641	0.1322	0.0708		0.0439	430
	(0.0322)	(0.0491)	(0.1013)	(0.0273)	(0.053)	(0.078)			
$F_{8,t}$	0.0323	-0.0021	0.3922	-0.0216	0.0387	0.4258		0.3158	430
	(0.0187)	(0.0284)	(0.0419)	(0.0169)	(0.0272)	(0.0419)			
Panel B: Predictive power for credit spread sorted decile portfolio returns									
$r^{S1}_{t-2\to t+1}$	0.0118	-0.0093	-0.0012	0.0049	-0.0009	0.0022	0.0165	0.0302	426
	(0.0057)	(0.0063)	(0.0104)	(0.0037)	(0.0068)	(0.0114)	(0.0023)		
$r^{S2}_{t-2\to t+1}$	0.0149	-0.0115	-0.0069	0.0093	0.0037	-0.0108	0.0200	0.0364	426
	(0.0080)	(0.0091)	(0.013)	(0.0052)	(0.0097)	(0.0145)	(0.0027)		
$r^{S3}_{t-2\to t+1}$	0.0117	-0.0140	-0.0078	0.0081	0.0038	-0.0072	0.0208	0.0177	426
	(0.0083)	(0.0103)	(0.0145)	(0.0061)	(0.0107)	(0.0161)	(0.0029)		
$r^{S4}_{t-2\to t+1}$	0.0124	-0.0108	-0.0072	0.0081	0.0066	-0.0159	0.0216	0.0166	426
	(0.0078)	(0.0109)	(0.0142)	(0.0064)	(0.0107)	(0.0163)	(0.0029)		
$r^{S5}_{t-2\to t+1}$	0.0097	-0.0122	-0.0165	0.0111	0.0036	-0.0112	0.0228	0.0148	426
	(0.0078)	(0.011)	(0.0159)	(0.0065)	(0.0109)	(0.0171)	(0.0030)		
$r^{S6}_{t-2\to t+1}$	0.0071	-0.0164	-0.0132	0.0109	-0.0012	-0.0076	0.0230	0.0117	426
	(0.007)	(0.011)	(0.0159)	(0.0065)	(0.0113)	(0.0174)	(0.0031)		
$r^{S7}_{t-2\to t+1}$	0.0035	-0.0230	-0.0114	0.0128	-0.0047	-0.0080	0.0232	0.0169	426
	(0.0063)	(0.0129)	(0.0156)	(0.0072)	(0.0116)	(0.0177)	(0.0031)		
$r^{S8}_{t-2\to t+1}$	-0.0015	-0.0219	-0.0228	0.0105	-0.0037	-0.0175	0.0260	0.0144	426
	(0.0061)	(0.0136)	(0.0167)	(0.0071)	(0.0113)	(0.0176)	(0.003)		
$r^{S9}_{t-2\to t+1}$	-0.0056	-0.0308	-0.0180	0.0140	-0.0070	-0.0191	0.0259	0.0171	426
	(0.0081)	(0.0162)	(0.0214)	(0.0092)	(0.0139)	(0.0219)	(0.0033)		
$r^{S10}_{t-2\to t+1}$	-0.0411	-0.0536	0.0139	-0.0077	-0.0269	-0.0289	0.0340	0.0167	426
	(0.0202)	(0.0321)	(0.0440)	(0.0204)	(0.0285)	(0.0547)	(0.0082)		

Table 7. **Tests Using the Long-Run Risk Measure Based on VAR**

This table presents GMM cross-sectional test results using the long-run risk measure based on VAR. The long-run consumption risk factor is measured as $(\hat{E}_{t+1} - \hat{E}_t)\sum_{s=0}^{\infty}\delta^s(c_{t+1+s} - c_{t+s})$. The quantity of risk is jointly estimated with parameters ζ and γ using GMM. Consumption of wealthy households defined as the top 30% of asset holders from CEX data is used. 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 5 long-term reversal 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 $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N}E(R_i^e)^2}$. '$\bar{R}^2$ with same γ' and '$\frac{RMSE}{RMSR}$ with same γ' report the pricing performance by imposing γ estimated using all portfolios. Time period spans from March 1984 to December 2019. 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	Reversal portfolios	All portfolios
ζ (%)	0.75	0.51	0.67	0.89	0.60	0.69	0.64	0.74
	[0.41 1.01]	[0.09 0.80]	[0.21 1.36]	[0.60 1.16]	[0.36 1.16]	[0.13 0.92]	[0.27 0.96]	[0.43 1.12]
γ	19.6	25.2	24.5	14.0	30.6	18.9	26.5	19.7
	[8.7 43.7]	[7.9 62.3]	[-23.9 68.9]	[-1.8 37.1]	[-17.1 43.9]	[5.3 63.7]	[13.3 40.4]	[4.0 41.8]
$\bar{R}^2$	0.96	0.99	0.26	0.88	0.90	0.92	0.64	0.83
	[0.49 0.98]	[0.56 0.99]	[0.00 0.92]	[0.04 0.97]	[0.01 0.97]	[0.49 0.99]	[0.20 0.92]	[0.07 0.89]
$\bar{R}^2$ with same γ	0.96	0.94	0.25	0.71	0.78	0.91	0.60	0.83
$\frac{RMSE}{RMSR}$	0.06	0.03	0.16	0.05	0.05	0.09	0.16	0.11
$\frac{RMSE}{RMSR}$ with same γ	0.06	0.10	0.16	0.08	0.09	0.11	0.17	0.11
Number of assets	10	5	5	5	5	5	5	40
Number of asset-month	4,260	2,130	2,130	2,130	2,070	2,130	2,090	16,940

Table 8. **Tests Using the Long-Run Risk Measure based on VAR with Different EIS Coefficients**

This table presents the GMM cross-sectional test results using the long-run risk measure based on VAR with different EIS coefficients. To allow EIS to be different from one, we estimate the following log SDF: $s_{t+1} \approx (1-\gamma)\lambda(\delta)w_{t+1}+(1/\rho-1)(\frac{1}{2}w'_{t+1}\Theta_0 w_{t+1}+w'_{t+1}\Theta_1 x_t+\theta_1 x_t+\theta_2 w_{t+1})$. The quantity of risk is jointly estimated with parameters of ζ and γ using GMM. Consumption of wealthy households defined as the top 30% of asset holders from CEX data is used. 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 5 long-term reversal 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 March 1984 to December 2019. Unconditional pricing errors ζ are multiplied by 100 for ease of exposition.

Assets	EIS = 0.3	EIS = 0.5	EIS = 0.7	EIS = 1	EIS = 1.5	EIS = 2
ζ (%)	0.93	0.85	0.80	0.74	0.69	0.66
	[0.66 1.29]	[0.60 1.20]	[0.54 1.15]	[0.43 1.12]	[0.36 1.10]	[0.34 1.10]
γ	14.6	16.8	18.2	19.7	21.1	21.9
	[4.6 24.3]	[4.4 31.2]	[4.2 36.7]	[4.0 41.8]	[3.8 41.4]	[3.8 40.3]
$\bar{R}^2$	0.78	0.81	0.82	0.83	0.84	0.84
	[0.07 0.86]	[0.07 0.87]	[0.07 0.88]	[0.07 0.89]	[0.07 0.89]	[0.07 0.89]
$\frac{RMSE}{RMSR}$	0.13	0.12	0.12	0.11	0.11	0.11
Number of assets	40	40	40	40	40	40
Number of asset-month	16,940	16,940	16,940	16,940	16,940	16,940

Table 9. **Test Accounting for Skewness**

This table reports a GMM cross-sectional regression result that accounts for skewness of bond returns: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{1}{2}\hat{E}[r^2_{i,t+1}] - \frac{1}{2}\hat{E}[r^2_{f,t}] = \zeta + (\gamma - 1)\hat{E}[\epsilon_{c,t\to t+S}(r_{i,t+1} - r_{f,t+1})] - \frac{1}{2}(1-\gamma)^2\hat{E}[\epsilon^2_{c,t\to t+S}(r_{i,t+1} - r_{f,t})] + \frac{1}{2}(\gamma - 1)\hat{E}[\epsilon_{c,t\to t+S}(r^2_{i,t+1} - r^2_{f,t})] + e_i$ where $\epsilon_{c,t\to t+S} = \sum_{s=0}^{S-1}\delta^s(c_{t+1+s} - c_{t+s}) - \mu_{\sum_{s=0}^{S-1}\delta^s(c_{t+1+s}-c_{t+s})}$, $r_{i,t+1}$ is the quarterly log return of an asset i, $r_{f,t}$ is the quarterly log rate of 30-day T-bill, $\delta = 0.95^{1/4}$, and c_t is the log consumption. The long-run consumption risk factor is measured by the discounted cumulative 20-quarter consumption growth ($S = 20$). Consumption of wealthy households defined as the top 30% of asset holders from CEX data is used. The quantity of risk is jointly estimated with parameters ζ and γ. Test assets are 40 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 5 long-term reversal portfolios. Reported are the intercepts ζ and implied risk-aversion coefficient 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 March 1984 to December 2019. Unconditional pricing errors ζ are multiplied by 100 for ease of exposition.

ζ (%)	1.25
	[0.17 0.86]
γ	8.1
	[3.1 9.7]
$\bar{R}^2$	0.38
	[0.05 0.55]
$\frac{RMSE}{RMSR}$	0.21
Number of assets	40
Number of asset-month	14,660

Table 10. **Test Using International Corporate Bonds**

This table reports GMM cross-sectional regression results using 40 characteristics-sorted portfolios based on 30 countries with different long-run horizons S: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} = \zeta + (\gamma - 1)\hat{cov}(\sum_{s=0}^{S-1} \delta^s (c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) + e_i$ where $r_{i,t+1}$ is the quarterly log return of an asset i, $r_{f,t}$ is the quarterly log rate of 30-day T-bill, $\delta = 0.95^{1/4}$, c_t is the log consumption. The long-run consumption risk factor is measured by the discounted cumulative consumption growth over multiple horizons $\sum_{s=0}^{S-1} \delta^s (c_{t+1+s} - c_{t+s})$. The quantity of risk is jointly estimated with parameters ζ and γ using GMM. Consumption of wealthy households defined as the top 30% of asset holders from CEX data is used. Test assets are 40 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 5 long-term reversal portfolios. 30 countries are Australia, Belgium, Brazil, Canada, Chile, China, Colombia, France, Germany, Hong Kong, India, Israel, Italy, Japan, Malaysia, Mexico, Netherlands, Norway, Peru, Qatar, Russia, Singapore, South Korea, Spain, Sweden, Switzerland, Thailand, Turkey, United Arab Emirates, and United Kingdom. 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 1997 to December 2017. Unconditional pricing errors ζ are multiplied by 100 for ease of exposition.

S (quarters) =	1	2	4	8	12	16	20	24
ζ (%)	0.89	0.68	0.89	1.13	1.16	0.95	0.92	1.15
	[0.33 1.51]	[0.28 1.19]	[0.41 1.31]	[0.46 1.49]	[0.46 1.56]	[0.48 1.43]	[0.41 1.29]	[0.47 1.69]
γ	32.1	15.0	18.4	32.2	-0.9	8.0	11.0	13.9
	[-13.0 58.8]	[-0.4 37.5]	[-1.5 29.0]	[-27.3 56.8]	[-26.9 43.9]	[-3.4 30.0]	[-3.3 28.4]	[-17.3 40.8]
$\bar{R}^2$	0.29	0.71	0.49	0.23	0.00	0.29	0.46	0.15
	[0.00 0.83]	[0.02 0.92]	[0.01 0.84]	[0.00 0.83]	[0.00 0.78]	[0.00 0.74]	[0.01 0.90]	[0.00 0.72]
$\frac{RMSE}{RMSR}$	0.24	0.15	0.20	0.25	0.28	0.20	0.19	0.24
Number of assets	40	40	40	40	40	40	40	40
Number of asset-month	9,435	9,435	9,435	9,435	9,075	8,595	8,115	7,635

Table 11. **Time-Series Regressions Using Other Factors and Long-Run Risk Factor**

This table reports time-series regressions of other factors on the tradable long-run risk factor in Panel A for each factor i: $F_{i,t+1} = \alpha + \beta X_{t+1} + \epsilon_{t+1}$. We also regress the tradable long-run risk factor on other factors in Panel B for each factor i: $X_{t+1} = \alpha + \beta F_{i,t+1} + \epsilon_{t+1}$. To estimate the tradable long-run risk factor X_{t+1}, long-run consumption risk measures are regressed on excess returns of 6 bond portfolios sorted on maturity and credit rating over the CEX sample period (March 1984 – December 2019), and then the coefficients are used to construct tradable long-run risk factor for April 1973 and December 2019. Panels A1 and B1 report results using the unconditional long-run risk measure which is the discounted cumulative consumption growth over 20-quarter horizons $\sum_{s=0}^{19} \delta^s (c_{t+1+s} - c_{t+s})$. Panels A2 and B2 report results using the conditional long-run risk measure $(\hat{E}_{t+1} - \hat{E}_t) \sum_{s=0}^{\infty} \delta^s (c_{t+1+s} - c_{t+s})$ based on VAR. Factors that we consider are intermediary capital risk factor by He, Kelly, and Manela (2017), Fama-French 7 factors (5 factors from Fama and French (2015) in addition to DEF and TERM), aggregate corporate bond excess returns, downside, and credit rating factors. Reported are average returns of each tradable factor, the intercepts α and coefficient β with bootstrapped standard errors computed with 5,000 replications. Average returns of factors and α are multiplied by 100 for ease of exposition.

Factors	HKM	SMB	HML	DEF	TERM	RMW	CMA	BOND-MKT	DOWNSIDE	CREDIT
Panel A: Regression of Other Factors on the Consumption-Mimicking Portfolio Returns										
A1: CEX unconditional Long-run risk measure										
Avg.	1.79	0.50	0.97	0.03	1.00	0.84	0.94	0.87	1.10	0.57
Returns (%)	(0.33)	(0.33)	(0.28)	(0.09)	(0.25)	(0.25)	(0.19)	(0.20)	(0.28)	(0.18)
α (%)	-0.39	0.25	0.81	-0.32	0.43	1.08	0.97	-0.08	-0.12	-0.06
	(0.26)	(0.36)	(0.29)	(0.22)	(0.48)	(0.24)	(0.22)	(0.19)	(0.33)	(0.38)
β	3.22	0.38	0.24	0.52	0.84	-0.35	-0.05	1.40	1.72	0.93
	(0.36)	(0.15)	(0.09)	(0.26)	(0.46)	(0.11)	(0.11)	(0.15)	(0.42)	(0.44)
Adj. R^2	0.59	0.02	0.00	0.16	0.08	0.02	0.00	0.52	0.30	0.16
A2: CEX conditional Long-run risk measure										
Avg.	1.74	0.50	0.97	0.03	1.00	0.84	0.94	0.87	1.10	0.57
Returns (%)	(0.36)	(0.35)	(0.30)	(0.09)	(0.27)	(0.27)	(0.21)	(0.21)	(0.30)	(0.21)
α (%)	-0.96	-0.14	0.84	-0.48	0.83	1.33	1.02	-0.10	-0.81	-0.66
	(0.21)	(0.36)	(0.35)	(0.21)	(0.62)	(0.35)	(0.24)	(0.25)	(0.40)	(0.42)
β	5.30	1.26	0.26	0.99	0.33	-0.95	-0.15	1.89	3.55	2.42
	(0.40)	(0.13)	(0.19)	(0.34)	(0.88)	(0.22)	(0.12)	(0.28)	(0.61)	(0.65)
Adj. R^2	0.69	0.08	0.00	0.25	0.00	0.07	0.00	0.39	0.57	0.44
Panel B: Regression of the Consumption-Mimicking Portfolio Returns on Each of Other Factors										
B1: CEX unconditional Long-run risk measure										
α (%)	0.35	0.65	0.65	0.67	0.57	0.73	0.69	0.36	0.51	0.58
	(0.11)	(0.11)	(0.1)	(0.11)	(0.11)	(0.09)	(0.11)	(0.07)	(0.14)	(0.12)
β	0.18	0.05	0.03	0.32	0.10	-0.06	-0.01	0.37	0.18	0.17
	(0.02)	(0.03)	(0.01)	(0.06)	(0.06)	(0.06)	(0.02)	(0.03)	(0.06)	(0.04)
Adj. R^2	0.59	0.02	0.00	0.16	0.08	0.02	0.00	0.52	0.30	0.16
B2: CEX conditional Long-run risk measure										
α (%)	0.28	0.48	0.50	0.50	0.49	0.57	0.52	0.33	0.36	0.41
	(0.03)	(0.06)	(0.05)	(0.06)	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
β	0.13	0.07	0.01	0.25	0.02	-0.07	-0.02	0.21	0.16	0.18
	(0.01)	(0.02)	(0.01)	(0.05)	(0.04)	(0.03)	(0.01)	(0.04)	(0.02)	(0.02)
Adj. R^2	0.69	0.08	0.00	0.25	0.00	0.07	0.00	0.39	0.57	0.44

Table 12. **Test Using Illiquidity Portfolios as Test Assets**

This table reports GMM cross-sectional regression results using illiquidity portfolios as test assets: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\hat{\sigma}^2(r_{i,t+1})}{2} - \frac{\hat{\sigma}^2(r_{f,t})}{2} = \zeta + (\gamma - 1)\hat{cov}(\sum_{s=0}^{S-1} \delta^s(c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) + e_i$ where $r_{i,t+1}$ is the quarterly log return of an asset i, $r_{f,t}$ is the quarterly log rate of 30-day T-bill, $\delta = 0.95^{1/4}$, c_t is the log consumption. The long-run consumption risk factor is measured by the discounted cumulative consumption growth $\sum_{s=0}^{S-1} \delta^s(c_{t+1+s} - c_{t+s})$ where $S = 20$ quarters for CEX and $S = 8$ quarters for NIPA. The column 'CEX' reports the result using the consumption growth of wealthy households defined as the top 30% of asset holders from CEX data. The column 'NIPA' reports using the consumption growth of aggregate households from NIPA. The quantity of risk is jointly estimated with parameters ζ and γ using GMM. Test assets are 5 Roll measure of illiquidity-sorted portfolios, 5 age sorted portfolios, 5 issue amount sorted portfolios, and 5 noise factor Hu, Pan, and Wang (2013) beta-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 March 1984 to December 2019 for CEX and from February 1973 to December 2019 for NIPA. Unconditional pricing errors ζ are multiplied by 100 for ease of exposition.

Data	CEX	NIPA
ζ (%)	0.46	1.29
	[0.21 1.60]	[0.47 1.48]
γ	27.9	-27.0
	[-8.3 38.5]	[-54.9 83.1]
$\bar{R}^2$	0.82	0.33
	[0.02 0.92]	[0.00 0.78]
$\frac{RMSE}{RMSR}$	0.12	0.29
Number of assets	20	20
Number of asset-month	5,940	7,930

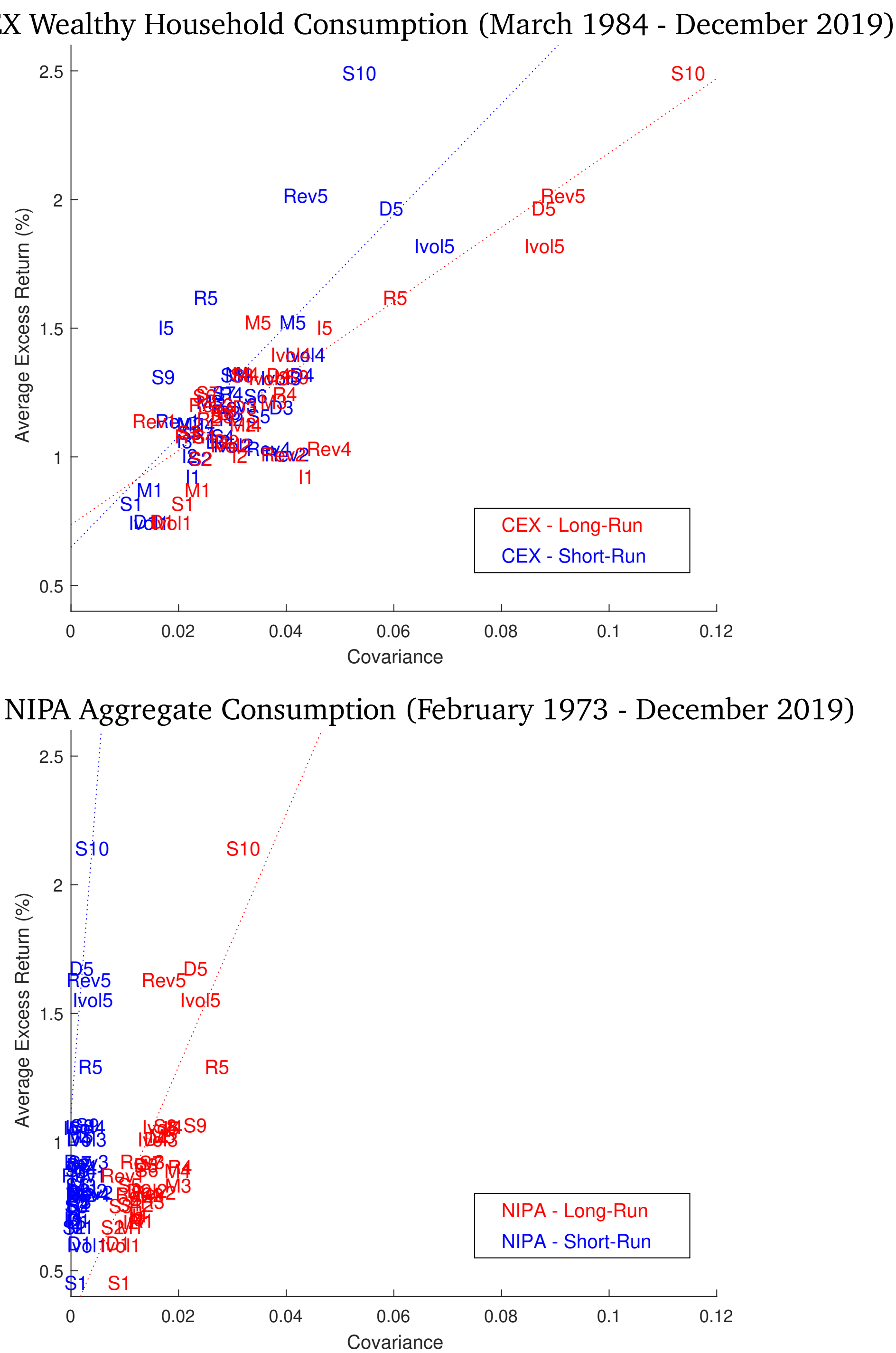

Figure 1. **Average Bond Returns and Covariances Between Bond Returns and Consumption Growth**

This figure plots the average bond excess returns (quarterly) against covariances of excess returns with the short-run ($c_{t+1} - c_t$) or long-run consumption growth rate ($\sum_{s=0}^{S-1} \delta^s (c_{t+1+s} - c_{t+s})$, where $S = 20$ quarters for CEX and $S = 8$ quarters for NIPA). Dotted line is from an OLS regression.

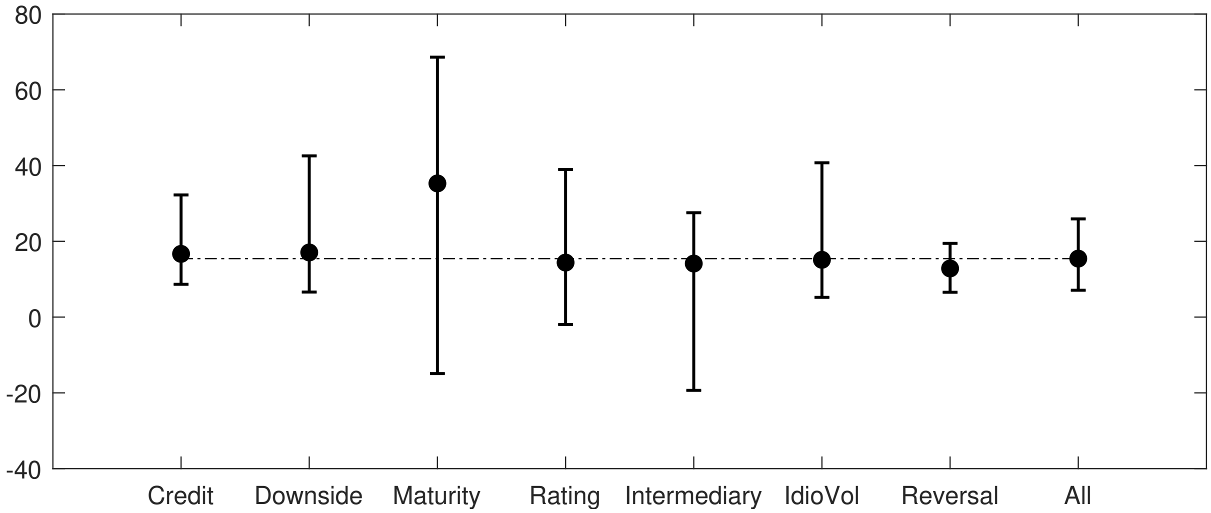

Figure 2. **Risk-Aversion Coefficients by Each Portfolio Group**

This figure plots the implied risk-aversion coefficients from GMM cross-sectional regressions for each portfolio group with two standard error bounds.

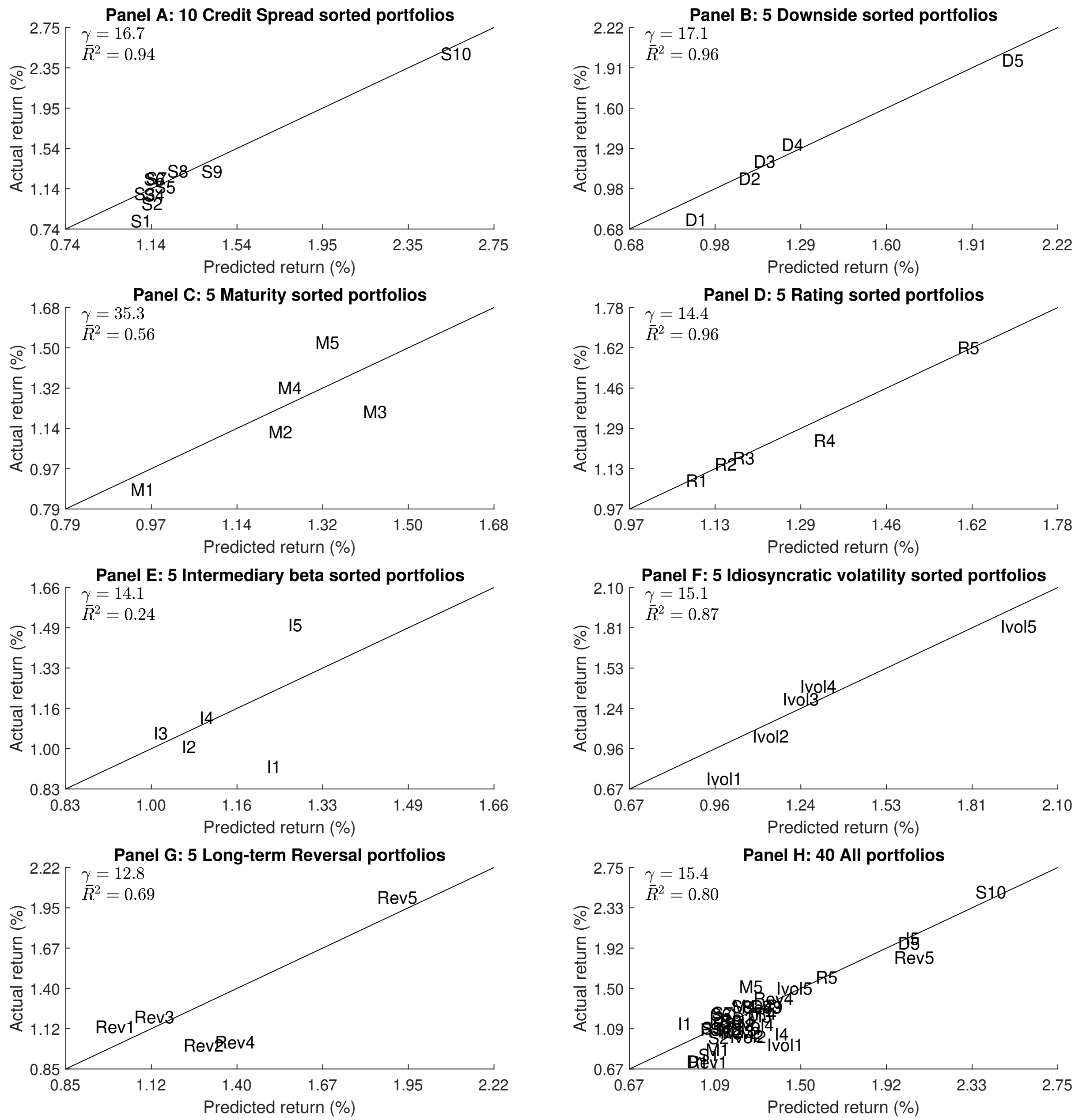

Figure 3. **Fitted and Average Returns of Bonds by Long-Run Risk Using Wealthy Households' Consumption**

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 wealthy households' consumption and the GMM estimation.

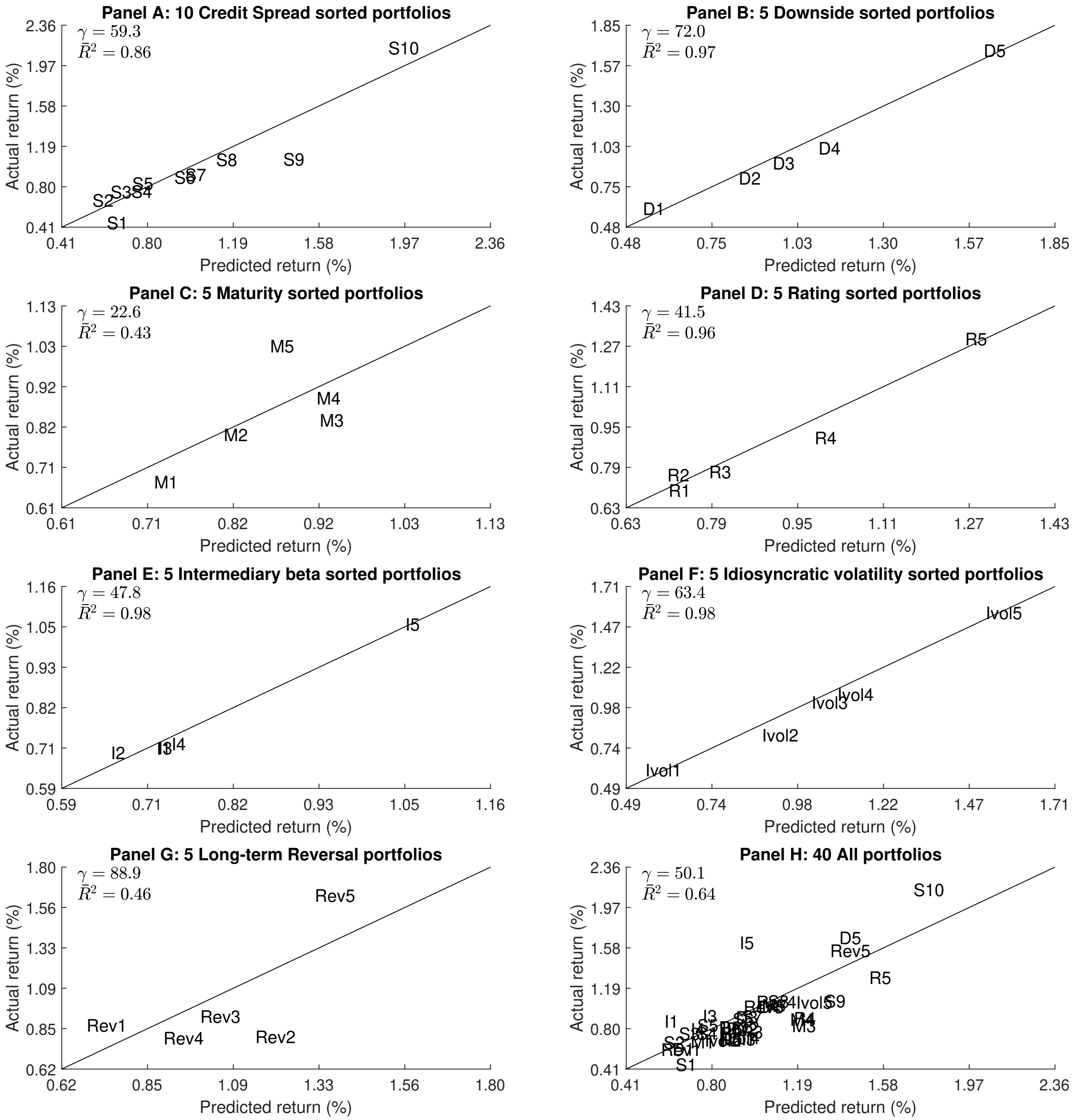

Figure 4. **Fitted and Average Returns of Bonds by Long-Run Risk Using Aggregate Consumption**

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 NIPA aggregate consumption and the GMM estimation.

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Internet Appendix to "A One-Factor Model of Corporate Bond Premia"

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This appendix contains additional results and tables that were referred to in the article. The body of the appendix consists of following sections:

I Detailed description of the data used in the paper

II Analysis on the behavior of consumption growth

III Theoretical motivation: calibrating the long-run risk model to corporate bond risk premiums

IV Identification of bondholders

V Alternative GMM estimates

VI Two-pass regressions on betas and price of risk estimates

VII Estimation results for VAR

Furthermore, the appendix contains a few tables that presents additional results mentioned in the paper.

I. Data

In this Appendix section, we describe the procedure to select data sets from the original source and remove potential errors.

I.A Lehman Brothers Database

The Lehman Brothers database provides monthly quotes for flat prices of corporate bonds and other bonds from January 1973 to March 1998. To select corporate bonds, we use the industry classification assigned by Lehman Brothers. Specifically, we use bonds classified as "industrial", "telephone utility", "electric utility", "utility (other)", "finance",[26] and remove the rest because bonds in the remainders are issued by government entities. After the removal of non-corporate bonds, we find that there are no observations in August 1975 and December 1984, and thus we do not compute monthly returns in August and September 1975, December 1984, and January 1985.

[26] These industries correspond to the industry code of 3,4,5,6,7, respectively.

The database does not include the frequency or exact dates of coupon payments, but does include accrued interest at the end of a month as well as monthly returns. We calculated ourselves month-end accrued interest assuming coupon payments are semi-annual, and find that correlation between our values and those in the database is 0.99. Thus, for consistency, we use monthly returns calculated ourselves as in Eq. (1).

The database includes the indicator for the observation being quote or matrix prices, and for the bonds being callable or not. As shown in Chordia et al. (2017), these distinctions do not lead to a significant difference in cross-sectional return predictability, and thus we include observations for matrix prices and callable bonds.

Lehman Brothers data also provides information on bond characteristics, such as amount outstanding, credit rating, offering, and maturity date.

I.B NAIC

NAIC data set includes transaction data of corporate bonds transacted by insurance companies from January 1994 to December 2014. The data field consists of transaction date, bond's CUSIP, transaction price, and volume. First, we construct daily price data by taking the volume-weighted average of all transactions. We do not impose cutoff based on transaction volume because we know a priori that these transactions are all institutional.

To construct monthly returns, we use the last trading date in the last 5 business days in a month as a month-end price observation for the bond. To calculate monthly returns, we consider two cases following Bai, Bali, and Wen (2019). First, a monthly return in month t can reflect a change from the month-end price in $t-1$ to the month-end price in t. If such a return is missing, we then consider the second case in which a monthly return is measured from the beginning of a month in $t+1$ to the end of month in $t+1$. The beginning of month price is the first daily price in the first 5 business days in a month. If a return in the second case is also missing, then we treat a return in the month as missing.

To select the subsample of corporate bonds in NAIC that satisfy our selection criteria, we merge NAIC transaction data to Mergent FISD data. We use the information regarding coupons in FISD to calculate month-end accrued interest and a return as in Eq. (1).

I.C DataStream

DataStream provides a monthly quote for a clean price of corporate bonds from January 1990 to September 2011. We find that the quotes for some bonds are extremely stale, and the clean price does not change for a prolonged time. Thus, we delete observations if the clean price does not change for three months or more.

After removing stale prices, we select a subsample of corporate bonds that we can merge to the Mergent FISD data as we do for the NAIC data set. We calculate accrued interest and monthly returns as in Eq.(1).

I.D TRACE

Enhanced TRACE provides all transactions data for corporate bonds from July 2002 to December 2019. The end of the sample period is defined by the availability of consumption data. Following Bessembinder et al. (2008), we use transactions with volume above $100,000 for more accurate information and calculate the volume-weighted average price on a day for the daily price data. We follow Dick-Nielsen (2009) to clean the data, removing cancelled transactions, and use corrected prices. Furthermore, we remove transactions with a when-issued condition, those with a special trading condition, locked-in trades, trade where the price includes commissions to dealers.

The procedure to transform daily price data to monthly returns is the same as we do for NAIC data. By merging TRACE data to Mergent FISD, we select bonds that satisfy our selection criteria.

I.E Mergent FISD

Mergent FISD provides data on (mostly) static bond characteristics. Thus, we merge Mergent FISD to NAIC, DataStream, and TRACE to augment the information other than flat prices, as well as to select a subsample of bonds that satisfy our selection criteria.

First, we describe the selection criteria for bonds in our analysis. We use a corporate bond (`bond_type='CDEB'or'CMTN'or'CMTZ'`) with fixed coupons (`coupon_type='F'`), which is not convertible (`convertible='N'`), not an asset-backed security (`asset_backed='N'`), not Yankee bond (`yankee='N'`), not issued by Canadian issuers (`canadian='N'`), U.S. dollar denominated (`foreign_currency='N'`), not puttable (`putable='N'`), and not a junior bond (`security_level~='JUN','SUB'or'JUNS'`).

Next, for bonds that meet our selection criteria, we obtain information for bond characteristics such as annual coupon rates, frequency of coupon payments, maturity date, offering date, the historical credit rating, and the historical amount outstanding. For bonds with missing amount outstanding information in the file, we set the amount outstanding equal to the face value at issue.

I.F Combined Data

After calculating monthly returns for each data set, we combine these four into one data set. When there are overlaps in the data sets, we prioritize in the following order: i) Lehman Brothers, ii) TRACE, iii) NAIC, and iv) DataStream. We then remove returns if they involve a monthly price below $5 or above $1,000 for the par value of $100 or if a bond's time to maturity is less than a year.

After the data sets are combined, we have 2,297,675 bond-month observations for 38,955 bonds and 7,995 issuers (as identified by the first six-digit CUSIP). Table IA7 reports the summary statistics of monthly bond returns in percentage form for all data sets as well as each individual data set. Table IA8 provides the summary statistics of the 7 portfolios.

I.G Consumer expenditure

In this subsection, we describe the Consumer Expenditure Survey (CEX) and our data selection procedure. The CEX is a nationwide household survey conducted by the U.S. Bureau of Labor Statistics (BLS), designed to provide detailed data on spending, income, and demographic features of consumers as well as their asset holding information.[27] In terms of interview frequency, a sample household is interviewed every three months over five times. Therefore, one can observe the quarterly consumption growth for each household. The BLS conducts the survey on a monthly basis by introducing new households and dropping old households who finish the last interview each month. Thus, we have quarterly consumption

[27]The data is publicly available at https://www.bls.gov/cex/.

growth at the monthly frequency with different sets of households each month.

The consumption in our study is nondurables and services from the CEX consumption categories. Following prior studies (e.g., Attanasio and Weber, 1995; Vissing-Jørgensen, 2002; Malloy, Moskowitz, and Vissing-Jørgensen, 2009), we exclude housing expenses (but not costs of household operations), medical care costs, and education costs since these cost items have significant durable components. We also exclude transportation costs which include vehicles and related costs (but not gasoline, oil, and public transportation) to match the definition of nondurables and services in NIPA. All nominal values are deflated using the 2012 value of USD. To adjust the seasonality of consumption, we regress the change in real per capita household consumption on a set of seasonal dummies and use the residual as our quarterly consumption growth measure.

We apply similar sampling procedures as in Malloy, Moskowitz, and Vissing-Jørgensen (2009) as follows. We compute the quarterly consumption growth ratio $C_{i,t+1}/C_{i,t}$ for each household and remove extreme outliers where the consumption growth ratio is less than 0.2 or above 5.0. Moreover, nonurban households and households residing in student housing are dropped. There was a change in household identification numbers in the first quarter interview of 1986. While Malloy, Moskowitz, and Vissing-Jørgensen (2009) dropped sample households which did not finish the fifth interview before the change, we match two different identification numbers by exploiting two sets[28] of 1986Q1 interview files where one has the old identification numbers and the other has the new. To be specific, if two households from two different sets of interviews have the exact same answers for all 17 questions[29] in the same month, we identify them as the same households. As a result, we match identification numbers of 1,267 households out of 1,609 households who did not finish the interview before ID changes. To check the validity of this matching strategy, we apply the same rule

[28]CEX adds a quarterly Interview Survey files that appear twice, once as the fifth and final quarter of the previous year and once as the first quarter of the new year. They denote the final quarter of the previous year with "X" to indicate that this file differs from the same quarterly file of the previous calendar year release, because it uses the methodology for the new year.

[29]We choose the following questions which can possibly have various numeric or categorical answers and also all households fully answered: composition of earners, region, income class, building type, number of males age 16 and over, number of females age 16 and over, number of males age 2 through 15, number of females age 2 through 15, number of members under age 2, ethnic origin, family type, marital status, housing tenure, age, education, race, and interview number.

to interview files of different years where there are no ID number changes, we confirm that once we find two households from two sets of interviews that have the same answers to these questions in the same month, they are indeed the same households. Our final sample of households is 807,991 household-month observations with 281,677 unique households, spanning from March 1984 to December 2019.

II. Behavior of consumption shocks

In this section, we study the properties of various consumption risk factors. In particular, we aim to compare the wealthy households' long-run consumption growth with bondholders' consumption growth (Internet Appendix IV provides the details for this measure) and the NIPA aggregate consumption growth. We start by plotting the three-month moving averages of 20-quarter consumption growth of wealthy households, bondholders, and the 1-quarter and 20-quarter consumption growth NIPA data in Figure A.3. The plot for 20-quarter growth is forward-looking in the sense that the data point in (say) 2005Q1 is the cumulative growth from 2005Q1 to 2009Q4. From the plot, we can see that the wealthy households' and bondholders' consumption is much more volatile than NIPA consumption. In contrast, the NIPA 20-quarter growth is more smooth and does not necessarily go down during recessions.

To quantify the cyclicality of consumption growth, we run a regression of consumption growth on various macroeconomic variables

$$\sum_{s=0}^{19} \delta^s \Delta c_{t+s+1} = b_0 + b_1 x_{t+1} + u_{t+s+1},$$

where x_{t+1} includes excess returns on the bond market, stock market, changes in macroeconomic uncertainty of Jurado, Ludvigson, and Ng (2015), NBER recession dummies, term spreads, default spreads and the dividend-price ratio. The standard errors are Newey-West adjusted (with lags equal to twice the number of overlapping months) to account for overlapping observations.

Table IA9 , which is added to the paper as Table IA9, reports the estimated slope coefficient and the regression R-squared. Comparing the slope coefficients b_1 across consumption series, the bondholders' and wealthy households' consumption tend to be more sensitive to uncertainty- and default-related news than NIPA consumption. For example, when default spreads increase by one percentage point, wealthy households' long-run consumption, bondholders' long-run consumption, and NIPA long-run consumption decrease 1.00, 2.49, and 0.86 percentage points, respectively. The sensitivity to macroeconomic uncertainty, returns on the bond market, and stock returns have the same pattern although the coefficient on the stock returns is insignificant due to large volatility. It is interesting to note that the sensitivity of wealthy households and bondholders' consumption to the NBER recession dummy is not higher than the NIPA long-run consumption. However, this is expected because GDP growth (to which NIPA consumption contributes) is used to judge NBER recessions. As we show below, once we condition consumption on the same set of state variables, wealthy households' and bondholders' consumption becomes more cyclical than NIPA consumption. In sum, the better performance of the wealthy households and bondholders' consumption stems from the better link between uncertainty and default risk.

Next, we turn to VAR-implied expected consumption growth. We study the expected consumption growth of wealthy households implied from the VAR used in Section 3.3. For comparison, we use the same set of state variables in the VAR and estimate the forecasting regression in (3) and (4) using the NIPA aggregate consumption and bondholders' consumption. Because the set of state variables in x_t is fixed, their persistence encoded in matrix G is held constant across three consumption series.

In Figure A.4, we plot the estimated expected consumption growth for wealthy households, bondholders, and NIPA aggregate. We see that the VAR-based expectations of wealthy households' and bondholders' consumption are volatile and appear less persistent than the NIPA counterpart. To see what this finding implies for the asset prices, we rewrite the stochastic discount factor in the model:

$$
\begin{aligned}
s_{t+1} &= (1-\gamma)\lambda(\delta)w_{t+1}, \\
&= (1-\gamma)(\eta_0 + \delta U_c(I-\delta G)^{-1}H)w_{t+1}.
\end{aligned}
$$

In the long-run risk model of Bansal and Yaron (2004), shocks to long-run aggregate consumption growth are highly volatile despite the low predictability of consumption growth because of the persistence of the state variables. In the equation above, for the NIPA aggregate consumption, the predictability U_c is close to zero but eigenvalues of G are close to one, which makes the volatility of the shock $U_c(I - \delta G)^{-1}H$ relatively large. Thus, persistence is the key for the NIPA consumption-based long-run risk model to work.

In our setup, $(I - \delta G)^{-1}H$ is held fixed across three consumption series. Thus, despite the apparent difference in volatility of expected consumption growth, the persistence of the state variables is the same by construction. Instead, the difference across three series entirely comes from U_c, or how predictable they are with the same set of state variables. Because the magnitude of the elements in U_c is larger for wealthy households' and bondholders' consumption than for aggregate consumption, the volatility of the first two shocks is greater than the last ones.

To see this point, Panel A of Table IA10 reports the estimates of U_c for wealthy households', bondholders' and aggregate consumption. The magnitude of the elements of U_c is much larger for wealthy households' and bondholders' consumption than the NIPA aggregate consumption. For the first lag, wealthy households' and bondholders' consumption are more than ten times as sensitive to F_6 (the factor capturing second-difference of general price levels) and F_8 (the factor capturing stock prices, such as the S&P500 index) as aggregate consumption is. In addition, for the second lag, these two consumption series are much more sensitive to F_2 (the factor capturing labor market conditions, such as total non-farm payrolls).

Panel B of Table IA10 reports the product of the standard deviation of the principal components and the regression slope coefficients. Since the standard deviation for F_8 (0.111) is somewhat lower than the other two ($\sigma(F_2) = 0.283$, $\sigma(F_6) = 0.163$), their contribution is somewhat attenuated. Overall, wealthy households' and bondholders' consumption are more predictable than NIPA consumption, in the sense that their predictable components vary more significantly than that of aggregate consumption. This predictability, rather than persistence, is the reason why the model works with a relatively low risk aversion.

Lastly, we study the cyclicality of expected consumption growth. In Table IA11, we regress shocks to the VAR-implied long-run consumption growth $\varepsilon_{c,t+1} + \delta U_c(I - \delta G)^{-1}\varepsilon_{x,t+1}$

on the aggregate stock and bond market returns as well as changes in macroeconomic uncertainty. In addition, we regress the level of expected consumption growth, $E_t[c_{t+1} - c_t]$, on time-t variables that capture business cycle.

The first three columns of Table IA11 report the estimates for shocks to the long-run consumption growth. We find that the estimated slope coefficients are greater in magnitude for wealthy households' and bondholders' consumption than for NIPA consumption. However, since the principal components selected by the AIC criteria do not include uncertainty or bond-market information, the coefficients for the bond market returns and uncertainty shocks are insignificant.

The last four columns of Table IA11 report the univariate regression of the level of expected consumption growth on the dummy variable for NBER recessions, term spreads, default spreads, and the dividend-price ratio. We find that on all four business cycle proxies, the expected consumption growth for wealthy households and bondholders loads significantly negatively. These results show that the expected consumption growth for these households declines significantly during recessions or when the term spreads, the default spreads, and the dividend-price ratio is high. The expected growth for NIPA aggregate consumption growth is also negatively correlated with these variables, but the slope coefficients are less than a tenth in magnitude of those for wealthy households. In sum, expectations for wealthy households' and bondholders' consumption growth are more cyclical than the NIPA aggregate consumption growth. When conditioned on a relatively small set of state variables, the link between the VAR-based measure and uncertainty is attenuated. Therefore, we explicitly include uncertainty shocks in the VAR and report the results in Internet Appendix VII.

III. Theoretical motivation

We have provided empirical evidence that a one-factor model with long-run consumption growth explains the risk premiums on corporate bond portfolios. In this section, we examine whether our empirical findings are supported by theory. Recent equilibrium-based structural models of credit risk (e.g. Bhamra, Kuehn, and Strebulaev, 2010a,b; Chen, 2010; Elkamhi 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.

III.A 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 provide details on the model in the following subsections.

III.A.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

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

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

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

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.

III.A.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

$$\pi_t = (\beta e^{-\beta t})^{\frac{1-\gamma}{1-\frac{1}{\psi}}} C_t^{-\gamma} \left(p_{C,t} e^{\int_0^t p_{C,s}^{-1} ds}\right)^{-\frac{\gamma - \frac{1}{\psi}}{1-\frac{1}{\psi}}} \tag{III.3}$$

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 $(f_1, f_2) = (\lambda_2/p, \lambda_1/p)$.

III.A.3 Asset prices

The debt value B_{ν_t} is the present value of a perpetual coupon stream c until a 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.

$$\begin{aligned} B_{\nu_t} &= E_t[\int_t^{\tau_D} \frac{\pi_s}{\pi_t} c ds | \nu_t] + E_t[\frac{\pi_{\tau_D}}{\pi_t} \alpha_{\tau_D} A_{\tau_D} | \nu_t] \\ &= \frac{c}{r_{P,\nu_t}} (1 - \sum_{\nu_D=1}^{2} l_{D,\nu_t,\nu_D} q_{D,\nu_t,\nu_D}) \quad \forall \nu_t \in \{1,2\} \end{aligned} \tag{III.4}$$

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

$$s_{\nu_t} = \frac{c}{B_{\nu_t}} - r_{P,\nu_t} = r_{p,\nu_t} \frac{\sum_{\nu_D=1}^{2} l_{D,\nu_t,\nu_D} q_{D,\nu_t,\nu_D}}{1 - \sum_{\nu_D=1}^{2} l_{D,\nu_t,\nu_D} q_{D,\nu_t,\nu_D}} \tag{III.5}$$

The conditional levered equity risk premium in state ν_t is

$$\mu_{R,\nu_t} - r_{\nu_t} = \gamma \rho_{XC} \sigma_{R,\nu_t}^{B,s} \sigma_{C,\nu_t} + \mathit{\Pi}_{\nu_t} \quad \forall \nu_t \in \{1,2\} \tag{III.6}$$

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 $(\mathit{\Pi}_1, \mathit{\Pi}_2) = ((1-\omega^{-1})(\frac{S_2}{S_1} - 1)\lambda_1, (1-\omega)(\frac{S_1}{S_2} - 1)\lambda_2)$. 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., $\mathit{\Pi}_{\nu_t} = 0$.

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

$$S_{\nu_t} = (1-\eta)E_t[\int_t^{\tau_D} \frac{\pi_s}{\pi_t}(X_s - c)ds|\nu_t] \tag{III.7}$$
$$= A_{\nu_t}(X_t) - (1-\eta)\frac{c}{r_{P,\nu_t}} + \sum_{\nu_D=1}^{2} q_{D,\nu_t,\nu_D}[(1-\eta)\frac{c}{r_{P,\nu_D}} - A_{\nu_D}(X_{D,\nu_D})] \quad \forall \nu_t \in \{1,2\}$$

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

III.B 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 IA12 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.[30] For the same reason, as in these papers and our empirical setting, we set the EIS to be one. As for the coefficient of relative risk aversion, we let 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*

[30]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).

expected consumption and earnings growth rate.[31] 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 of all, our model calibration generates empirically observed levels of equity risk premium of 2.69%[32] 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 stem 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 A.1 shows the result. 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 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 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.

We do the same calibration exercise for equity and find that the contribution of the long-run risk for equity is always lower than its contribution for bonds, ranging from 88% and 90%. This result provides a rationale for why the long-run risk is more important for corporate bonds than equity from the theoretical perspective. The result is shown in Figure

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

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

A.2.

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 A.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 A.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.

IV. Measuring bondholders consumption

In this section, we explain details on how we identify bondholders in the CEX data based on the Survey of Consumer Finances (SCF). To identify likely bondholders in the CEX, we employ the imputation procedure widely used in the literature (e.g., Attanasio, Banks, and Tanner, 2002; Malloy, Moskowitz, and Vissing-Jørgensen, 2009; Elkamhi and Jo, 2019; Cole et al., 2020; Gaudio, Petrella, and Santoro, 2021). Specifically, we run a Probit regression of corporate bond ownership in the SCF data on households characteristics that are available in the CEX data as well. Next, we apply the estimated coefficients from the Probit regression to the CEX households to calculate the probability of corporate bond ownership for CEX households.

Table IA13 presents the descriptive statistics of non-corporate bondholders (Panel A), corporate bondholders (Panel B), non-equityholders (Panel C), equityholders that account for indirect holdings through retirement accounts (Panel D), and total respondents (Panel E) in SCF using 1992, 1995, 1998, 2001, 2004, 2007, 2010, 2013, 2016, and 2019 waves.[33] Corporate bond holders are defined as respondents who directly or indirectly hold corporate bonds through funds. Wealth is the value of checking, savings, mutual funds, stocks, and bonds. Income is the total household 12-month income before taxes. Dividend income is the total family annual dividend income. All dollar values are in 2019 dollars. Comparing Panel A with Panel B shows that corporate bondholders are generally much wealthier than non-corporate bondholders: The median wealth level of corporate bondholders is \$589,877.8 versus \$8,477.4 for non-corporate bondholders. Moreover, corporate bondholders have much higher incomes, are older, more educated, more likely to be white, have more kids, more likely to be married, and male. We exploit these stark differences in households characteristics, wealth, and income level between the two groups and run a Probit regression. Comparing Panel B and D shows that corporate bondholders' characteristics are different from equityholders. Corporate bondholders are wealthier and own an even higher value of stocks than equityholders.

Table IA14 presents the result from the Probit regression of households' corporate bond ownership on households characteristics. Note that for variables in dollar values, we take a ratio of the variable to the household's labor income since ratios can mitigate a measurement error in the level (e.g. Aguiar and Bils, 2015). Next, we define bondholders as households that have at least 10% probability of holding corporate bonds based on our estimates among asset holders. We use the threshold of 10% of owning corporate bonds since corporate bonds are not widely held by households. Indeed, the SCF data show that only 5.3% of households hold corporate bonds. Therefore, increasing the threshold results in a much lower number of samples and nosier estimates of bondholders' consumption.

[33] We start with the 1992 wave since previous waves do not distinguish corporate bonds from foreign bonds.

V. Estimates using reverse regressions

A consistent estimator of the risk-aversion coefficient γ can also be obtained by running the cross-sectional regression in (17) in reverse where long-run consumption risk is placed on the left-hand side:

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

Eq (17) and (V.1) 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.

Reverse regression results in Table IA15 show that the estimated γ is lower for S above 16 than it is for $S = 1$ with this alternative set of estimates for CEX consumption, confirming the main results. The point estimates for γ are somewhat greater than the main results, but they remain roughly in the same ballpark with $\gamma = 19$ with $S = 20$, and the confidence interval includes the point estimate in the main results ($\gamma = 15.4$). Therefore, our findings are robust to alternative estimation methods for model parameters.

VI. Two-pass regression

The risk-aversion coefficient γ is intuitive and easy to compare with the literature that calibrates the consumption-based asset pricing model. However, we cannot compare this 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 quarterly excess returns $r_{i,t+1} - r_{f,t}$ on the long-run consumption risk factor using the 20-quarter cumulative consumption growth of wealthy households $\sum_{s=0}^{19} \delta^s (c_{t+1+s} - c_{t+s})$.

$$r_{i,t+1} - r_{f,t} = a_i + \beta_i \left(\sum_{s=0}^{19} \delta^s (c_{t+1+s} - c_{t+s})\right) + u_{p,t+1}. \tag{VI.1}$$

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,

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

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 $\beta = 1$.

Table IA16 presents the price of risk based on the two-pass regressions in (VI.1) and (VI.2) using the discounted 20-quarter cumulative consumption growth as a risk factor. The estimated risk premium using all 40 portfolios is 11% per quarter which translates into 3.67% per month, which is statistically significantly different from zero as indicated by the 95% confidence interval. This estimate of the price of risk is far greater than the risk premiums on the corporate bond market portfolio of 0.39% and premiums on downside risk factor of 0.70% reported in Bai, Bali, and Wen (2019). This large price of risk is due to the high volatility of wealthy household consumption growth. In Table IA8, the volatility of quarterly consumption risk is above 8%, which is much higher than that of bond portfolio returns. Thus, a hypothetical security with $\beta = 1$ is much riskier than bond portfolios used in the literature.

The estimates for λ_1 for each sub-sample range from 9% to 27% per quarter, and the 95% confidence intervals for all of these estimates contain the full sample estimates of 11%. The cross-sectional $\bar{R}^2$ is 0.80 with a tight 95-percent confidence interval ranging from 0.26 to 0.90, suggesting a good fit of the model. Overall, these results suggest that the estimated risk premiums are consistent across the seven sets of test assets that we use, and the long-run risk is a priced factor in the cross-section of corporate bonds.

Table IA17 reports the two-pass regressions using shocks to expectation for the long-run consumption growth as a risk factor. We find that the estimated price of risk using all 40 portfolios is 12% per quarter, very similar but slightly higher than the price of risk of 11% per quarter in Table IA16 using unconditional long-run consumption growth. This difference is driven by lower correlations of shocks to expectation for the long-run consumption growth with asset returns than those of unconditional long-run consumption growth, which lower betas and raise the price of risk. As before, the estimated price of risk levels are consistent across test assets, demonstrating the consistent pricing performance of the long-run risk model for corporate bonds.

Table IA18 presents the results using NIPA aggregate consumption growth cumulated over 8 quarters. Even though estimated γ is greater for this factor, it is less volatile and thus the estimated price of risk is less than Table IA18.

VII. VAR estimation for the general EIS case

In this Appendix section, we discuss our VAR estimation for the general case where EIS is not equal to one. For this exercise, we rely on the stochastic discount factor for the long-run risk model with Epstein-Zin utility derived in Hansen et al. (2007), Hansen, Heaton, and Li (2008) as follows. The log consumption evolves according to:

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

where x_t is a state vector representing a persistent predictable component of consumption growth which evolves as:

$$x_{t+1} = G x_t + H w_{t+1} \tag{VII.2}$$

The first-order expansion of the logarithm of the stochastic discount factor without constant terms and '$c_{t+1} - c_t$' term that do not materially affect our result is

$$s_{t+1} \approx (1-\gamma)\lambda(\delta) w_{t+1} + \left(\frac{1}{\rho} - 1\right)\left(\frac{1}{2} w'_{t+1} \mathit{\Theta}_0 w_{t+1} + w'_{t+1} \mathit{\Theta}_1 x_t + \theta_1 x_t + \theta_2 w_{t+1}\right) \tag{VII.3}$$

where

$$
\begin{aligned}
\lambda(\delta) &= \eta_0 + \delta U_c (I - \delta G)^{-1} H \\
\Theta_0 &= (\gamma - 1) H' \Omega H \\
\Theta_1 &= (\gamma - 1) H' \Omega G \\
\theta_1 &= -U_c + (\gamma - 1)^2 \lambda(\delta) H' \Omega G \\
\theta_2 &= -(1-\gamma)\omega' H + U_v' H \\
\Omega &= \frac{1-\delta}{\delta} U_v U_v' + \delta G' \Omega G \\
U_v &= \delta (I - \delta G')^{-1} U_c' \\
\omega &= (I - \delta G')^{-1} \left(\frac{1-\delta}{\delta} \mu_v U_v + \delta(1-\gamma) G' \Omega H (\eta_0' + H' U_v)\right) \\
\mu_v &= \frac{\delta}{1-\delta} \left(\mu_c + \frac{1-\gamma}{2} |\lambda(\delta)|^2\right)
\end{aligned}
$$

The first term in (VII.3) represents the log SDF when EIS $= 1$. The second term arises when EIS $\neq 1$. With the assumption of EIS $= 1$, we only need to estimate the first term for the long-run consumption risk measure. We conduct the analysis for the general case where EIS $\neq 1$ by identifying w_{t+1} in the following way.

For the state vector x_{t+1}, we choose $F_{2,t+1}$, $F_{6,t+1}$, $F_{8,t+1}$ and their one month lags, factors from 160 macro and financial variables, given the ability of this set of variables to predict future consumption. Let $\epsilon_{c,t+1}$ and $\epsilon_{x,t+1} = [\epsilon_{F_2,t+1}, \epsilon_{F_6,t+1}, \epsilon_{F_8,t+1}, \epsilon_{F_2,t}, \epsilon_{F_6,t}, \epsilon_{F_8,t}]'$ denote error terms from (VII.1) and (VII.2), which are to be estimated by OLS equation by equation. They can be expressed by

$$
\begin{bmatrix} \epsilon_{c,t+1} \\ \epsilon_{x,t+1} \end{bmatrix} = \begin{bmatrix} \eta_0 \\ H \end{bmatrix} w_{t+1} \Longleftrightarrow \epsilon_{t+1} = M w_{t+1}
$$

Expanding matrices yields

$$\Longleftrightarrow \begin{bmatrix} \epsilon_{c,t+1} \\ \epsilon_{F_2,t+1} \\ \epsilon_{F_6,t+1} \\ \epsilon_{F_8,t+1} \\ \epsilon_{F_2,t} \\ \epsilon_{F_6,t} \\ \epsilon_{F_8,t} \end{bmatrix} = \begin{bmatrix} \eta_{0,c} & \eta_{0,F_2} & \eta_{0,F_6} & \eta_{0,F_8} & \eta_{0,F_{2,-1}} & \eta_{0,F_{6,-1}} & \eta_{0,F_{8,-1}} \\ H_{2,c} & H_{2,2} & H_{2,6} & H_{2,8} & H_{2,2,-1} & H_{2,6,-1} & H_{2,8,-1} \\ H_{6,c} & H_{6,2} & H_{6,6} & H_{6,8} & H_{6,2,-1} & H_{6,6,-1} & H_{6,8,-1} \\ H_{8,c} & H_{8,2} & H_{8,6} & H_{8,8} & H_{8,2,-1} & H_{8,6,-1} & H_{8,8,-1} \\ H_{2,-1,c} & H_{2,-1,2} & H_{2,-1,6} & H_{2,-1,8} & H_{2,-1,2,-1} & H_{2,-1,6,-1} & H_{2,-1,8,-1} \\ H_{6,-1,c} & H_{6,-1,2} & H_{6,-1,6} & H_{6,-1,8} & H_{6,-1,2,-1} & H_{6,-1,6,-1} & H_{6,-1,8,-1} \\ H_{8,-1,c} & H_{8,-1,2} & H_{8,-1,6} & H_{8,-1,8} & H_{8,-1,2,-1} & H_{8,-1,6,-1} & H_{8,-1,8,-1} \end{bmatrix} \begin{bmatrix} w_{c,t+1} \\ w_{F_2,t+1} \\ w_{F_6,t+1} \\ w_{F_8,t+1} \\ w_{F_2,t} \\ w_{F_6,t} \\ w_{F_8,t} \end{bmatrix}$$

Given $Var(w_{t+1}) = I$ and $Var(\epsilon_{t+1}) = MM'$, there are 28 equations and 49 unknowns. Therefore, we impose the following shock structure to identify ω.

$$\Longleftrightarrow \begin{bmatrix} \epsilon_{c,t+1} \\ \epsilon_{F_2,t+1} \\ \epsilon_{F_6,t+1} \\ \epsilon_{F_8,t+1} \\ \epsilon_{F_2,t} \\ \epsilon_{F_6,t} \\ \epsilon_{F_8,t} \end{bmatrix} = \begin{bmatrix} \eta_{0,c} & \eta_{0,F_2} & \eta_{0,F_6} & \eta_{0,F_8} & \eta_{0,F_{2,-1}} & \eta_{0,F_{6,-1}} & \eta_{0,F_{8,-1}} \\ H_{2,c} & H_{2,2} & H_{2,6} & H_{2,8} & H_{2,2,-1} & H_{2,6,-1} & H_{2,8,-1} \\ H_{6,c} & H_{6,2} & H_{6,6} & H_{6,8} & 0 & 0 & 0 \\ H_{8,c} & H_{8,2} & H_{8,6} & H_{8,8} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & H_{2,-1,2,-1} & 0 & 0 \\ 0 & 0 & 0 & 0 & H_{6,-1,2,-1} & H_{6,-1,6,-1} & 0 \\ 0 & 0 & 0 & 0 & H_{8,-1,2,-1} & H_{8,-1,6,-1} & H_{8,-1,8,-1} \end{bmatrix} \begin{bmatrix} w_{c,t+1} \\ w_{F_2,t+1} \\ w_{F_6,t+1} \\ w_{F_8,t+1} \\ w_{F_2,t} \\ w_{F_6,t} \\ w_{F_8,t} \end{bmatrix}$$

We do not impose a lower triangular matrix as usual in the structural VAR in order to plausibly assume that shocks at time $t+1$ do not have an impact on error terms at time t. By imposing the above structure, first η_0 and H are estimated from $Var(\epsilon_{t+1}) = MM'$ and then, w_{t+1} are estimated from $w_{t+1} = M^{-1}\epsilon_{t+1}$. Finally, other parameters and matrices in the second term in (VII.3) are computed.

Table IA5 reports variables and descriptions of 160 pre-selected macro and financial variables as well as the variance decomposition of $F_{2,t}$, $F_{6,t}$, $F_{8,t}$ with respect to 160 variables. Table IA19 reports R^2 and AIC from regressions of consumption growth on state variables to show how $F_{2,t}$, $F_{6,t}$, $F_{8,t}$ and their one month lags are selected for x_t. Table 6 reports the VAR estimation results and predictive regressions of credit spread sorted decile portfolios on state variables. Table IA6 reports the descriptive statistics of the long-run risk measure based on the VAR estimation.

Furthermore, we expand the VAR estimates to allow for volatility shocks that enter the SDF. Specifically, we include realized variance of monthly industrial production growth as an additional state variable in the VAR in (VII.2), while other state variables are kept unchanged. We then follow Bansal et al. (2014) and add additional shock to the SDF in (VII.3) to create an augmented SDF,

$$s_{t+1}^{BKSY} = s_{t+1} + \frac{1}{2}\chi(1-\gamma)^2 i_v' Q \epsilon_{t+1}, \tag{VII.4}$$

where s_{t+1} is the original SDF in (VII.3), χ is the ratio of variance of long-run consumption growth to variance of current consumption growth, i_v is an indicator vector that selects the entry for realized variance, and $Q \equiv \delta G(I - \delta G)^{-1}$.

The SDF in (VII.4) explicitly accounts for volatility news that is an additional shock to investors' marginal utility. However, we still restrict its loading as a function of the risk-aversion coefficient, γ, and thus the degrees of freedom in the model remain unchanged. Using the version of the model with EIS=1, we repeat the GMM estimates as we do for Table 7 and report the results in Table IA20.

In Table IA20, the estimated risk-aversion coefficient γ is 20.62, which is fairly close to the main VAR results in Table 7 (18.9). The cross-sectional R-squared is 0.85, which is also similar to Table 7. Therefore, our VAR results are robust to explicitly accounting for volatility shocks.

Table IA1. **GMM Cross-Sectional Regression Using 2020 Samples**

This table reports GMM cross-sectional regression results using available most recent samples in 2020 with different long-run horizons S: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} = \zeta + (\gamma - 1)\hat{cov}(\sum_{s=0}^{S-1} \delta^s (c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) + e_i$ where $r_{i,t+1}$ is the log return of an asset i, $r_{f,t}$ is the log rate of 30-day T-bill, $\delta = 0.95^{1/4}$ for CEX and $\delta = 0.95^{1/12}$ for NIPA, c_t is the log consumption. The long-run consumption risk factor is measured by the discounted cumulative consumption growth over multiple horizons $\sum_{s=0}^{S-1} \delta^s (c_{t+1+s} - c_{t+s})$. Panel A reports the results using the consumption growth of wealthy households defined as the top 30% of asset holders from CEX data. Panel B reports the results using the consumption growth of aggregate households from NIPA. The quantity of risk is jointly estimated with parameters ζ and γ using GMM. Test assets are 40 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 5 long-term reversal 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 March 1984 to February 2020 for CEX and from February 1973 to October 2020 for NIPA. Unconditional pricing errors ζ are multiplied by 100 for ease of exposition.

S (quarters)	1	2	4	8	12	16	20	24
Panel A: NIPA (aggregate consumption)								
ζ (%)	0.74	0.57	0.59	0.23	0.19	0.42	0.38	0.68
	[0.39 1.02]	[0.17 1.01]	[0.16 1.14]	[-0.2 0.97]	[-0.13 0.98]	[-0.08 1.27]	[-0.05 1.04]	[0.22 1.27]
γ	52.48	59.31	61.31	47.48	52.24	51.83	48.60	50.60
	[0 306.69]	[0.01 168.9]	[0.01 96.45]	[0.03 66.32]	[0.05 69.57]	[0.06 84.81]	[0.07 78.55]	[0.09 78.79]
$\bar{R}^2$	0.41	0.48	0.47	0.68	0.65	0.17	0.66	0.17
	[0.23 0.74]	[0.17 0.71]	[0 0.76]	[0.16 0.8]	[0.08 0.84]	[0 0.79]	[0.04 0.82]	[0 0.76]
$\frac{RMSE}{RMSR}$	0.24	0.22	0.23	0.19	0.19	0.30	0.18	0.29
Number of assets	40	40	40	40	40	40	40	40
Number of asset-month	21,760	21,680	21,440	20,960	20,480	20,000	19,520	19,040
Panel B: CEX (consumption of wealthy households)								
ζ (%)	0.72	0.46	0.84	0.99	0.95	0.48	0.72	0.74
	[0.5 1.3]	[0.13 1.19]	[0.42 1.22]	[0.64 1.38]	[0.52 1.74]	[0.13 0.94]	[0.41 0.95]	[0.24 1.11]
γ	22.66	23.29	17.17	21.74	16.96	19.89	15.45	23.56
	[-1.19 40.48]	[1.25 34.73]	[-4.83 32.01]	[-20.04 43.61]	[-20.79 37.89]	[4.43 29.73]	[7.32 26.41]	[5.9 45.25]
$\bar{R}^2$	0.32	0.71	0.21	0.29	0.13	0.71	0.81	0.61
	[0 0.65]	[0 0.93]	[0 0.74]	[0 0.67]	[0 0.54]	[0.05 0.89]	[0.25 0.9]	[0.08 0.79]
$\frac{RMSE}{RMSR}$	0.22	0.15	0.25	0.24	0.26	0.14	0.12	0.17
Number of assets	40	40	40	40	40	40	40	40
Number of asset-month	17,020	16,900	16,660	16,180	15,700	15,220	14,740	14,260

Table IA2. **Risk Aversion Estimates From Prior Studies**

This table reports risk aversion estimates from prior studies estimating risk aversion coefficients from the consumption-based asset pricing models. Numbers in bold denote estimates of risk aversion prior studies base on to claim support of the model. Square brackets denote boundaries of risk aversion for conditional risk-aversion specifications.

Study	Risk aversion	Specification	Asset Class	Consumption
Attanasio (1991)	168, 201, 259, 286	Unconditional	Equity	NIPA aggregate
Ferson and Harvey (1993)	42, 49, 80, 99, 169, 184	Unconditional	Equity	NIPA aggregate
Aït-Sahalia, Parker, and Yogo (2004)	**7**, **12**, ..., **20**, 50	Unconditional	Equity	Luxury goods
Aït-Sahalia, Parker, and Yogo (2004)	50, 173	Unconditional	Equity	NIPA aggregate
Duffee (2005)	-237, -181, -168, -31	Unconditional	Equity	NIPA aggregate
Duffee (2005)	[-88, -4]	Conditional	Equity	NIPA aggregate
Parker and Julliard (2005)	9 ($R^2 = 0.04$), 12 ($R^2 = 0.07$), **25**, 39	Unconditional	Equity	NIPA aggregate
Bansal, Kiku, and Yaron (2007)*	15, 16	Unconditional	Equity	NIPA aggregate
Malloy, Moskowitz, and Vissing-Jørgensen (2009)*	13 ($R^2 = 0.01$), 18 ($R^2 = 0.05$), ..., 541, 1,037	Unconditional	Equity	NIPA aggregate
Malloy, Moskowitz, and Vissing-Jørgensen (2009)*	-390, -346, . . . , **14**, **17**, **19**, 137	Unconditional	Equity	CEX stockholders
Nagel and Singleton (2011)	[-3000, -2000]	Conditional	Equity	NIPA aggregate
Nagel and Singleton (2011)	365	Unconditional	Equity	NIPA aggregate
Savov (2011)	**15**, **17**, **22**, **26**	Unconditional	Equity	Municipal solid waste (garbage)
Roussanov (2014)	[-250, 600]	Conditional	Equity	NIPA aggregate
Bednarek and Patel (2015)*	30, 31, 43, 48	Unconditional	Equity	NIPA aggregate
Calvet and Czellar (2015)*	27	Unconditional	Equity	NIPA aggregate
Kim and Lee (2016)*	80, 92	Unconditional	Equity	NIPA aggregate
Abhyank, Klinkowska, and Lee (2017)*	64, 103, 123	Unconditional	Equity	NIPA aggregate
Kroencke (2017)	**19**, **23**	Unconditional	Equity	Unfiltered NIPA aggregate
Malloy, Moskowitz, and Vissing-Jørgensen (2009)*	**13**	Unconditional	Government bonds	CEX stockholders
Malloy, Moskowitz, and Vissing-Jørgensen (2009)*	81	Unconditional	Government bonds	CEX aggregate
Abhyank, Klinkowska, and Lee (2017)*	51, 52	Unconditional	Government bonds	NIPA aggregate

Note: * denotes a paper that tests the long-run risk model of Bansal and Yaron (2004).

Table IA3. **Volatility and Sensitivity of Consumption Growth with Different Levels of Cutoff**

This table reports volatility of S-quarter growth rate of CEX wealthy households' consumption with different levels of a wealth cutoff in Panel A and time-series regressions of those consumption measures on aggregate bond returns over different long-run horizons S in Panel B,

$$\sum_{s=0}^{S-1} \delta^s (c_{t+1+s} - c_{t+s}) = b_0 + b_1 r_{t+1} + u_{t,t+1+S},$$

where $\delta = 0.95^{1/4}$. The values in parentheses are standard errors with the Newey-West $S \times 3$ -1 month lags.

S =	1	2	4	8	12	16	20	24
Panel A: Volatility of consumption growth								
CEX wealthy top 10	0.144	0.152	0.160	0.176	0.170	0.187	0.196	0.202
CEX wealthy top 30	0.083	0.088	0.086	0.089	0.089	0.088	0.088	0.084
CEX wealthy top 50	0.061	0.063	0.064	0.063	0.064	0.064	0.062	0.061
CEX wealthy top 70	0.051	0.054	0.056	0.052	0.055	0.054	0.053	0.053
Panel B: Sensitivity to corporate bond returns								
CEX wealthy top 10	0.089	0.405	0.505	-0.078	0.32	0.496	0.518	0.415
(s.e.)	(0.228)	(0.211)	(0.224)	(0.222)	(0.223)	(0.392)	(0.262)	(0.292)
R^2	$3.2{\times}10^{-4}$	0.006	0.008	$1.7{\times}10^{-4}$	0.003	0.006	0.006	0.004
CEX wealthy top 30	0.260	0.370	0.253	0.098	0.145	0.450	0.383	0.258
(s.e.)	(0.13)	(0.126)	(0.173)	(0.108)	(0.132)	(0.129)	(0.114)	(0.116)
R^2	0.008	0.015	0.007	0.001	0.002	0.023	0.016	0.008
CEX wealthy top 50	0.200	0.249	0.230	0.084	0.078	0.250	0.134	0.248
(s.e.)	(0.09)	(0.089)	(0.103)	(0.091)	(0.102)	(0.096)	(0.119)	(0.093)
R^2	0.009	0.013	0.011	0.002	0.001	0.013	0.004	0.015
CEX wealthy top 70	0.218	0.19	0.235	0.048	0.142	0.171	0.157	0.246
(s.e.)	(0.088)	(0.088)	(0.100)	(0.074)	(0.098)	(0.078)	(0.088)	(0.073)
R^2	0.016	0.011	0.016	0.001	0.006	0.009	0.008	0.020

Table IA4. **GMM Cross-Sectional Regression with Different Levels of Cutoff**

This table reports GMM cross-sectional regression results over different long-run horizons S with different levels of a wealth cutoff: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\hat{\sigma}^2(r_{i,t+1})}{2} - \frac{\hat{\sigma}^2(r_{f,t})}{2} = \zeta + (\gamma - 1)c\hat{o}v(\sum_{s=0}^{S-1} \delta^s(c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) + e_i$ where $r_{i,t+1}$ is the quarterly log return of an asset i, $r_{f,t}$ is the quarterly log rate of 30-day T-bill in Panels A, B, D and E while it is the log return on matching Treasury bonds in Panel C, $\delta = 0.95^{1/4}$, c_t is the log consumption. The long-run consumption risk factor is measured by the discounted cumulative consumption growth over multiple horizons $\sum_{s=0}^{S-1} \delta^s(c_{t+1+s} - c_{t+s})$. The quantity of risk is jointly estimated with parameters ζ, η, and γ using GMM. Test assets are 40 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 5 long-term reversal portfolios. Reported are the intercepts ζ, η and implied risk-aversion coefficients γ. 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 March 1984 to December 2019 for CEX and from February 1973 to December 2019 for NIPA. Unconditional pricing errors ζ and η are multiplied by 100 for ease of exposition.

S =		1	2	4	8	12	16	20	24
CEX wealthy top 10	γ	12.08	18.24	13.86	6.82	12.70	6.54	9.43	10.92
	$\bar{R}^2$	0.14	0.72	0.82	0.16	0.27	0.04	0.41	0.27
CEX wealthy top 30	γ	23.49	23.54	17.05	21.96	16.81	16.07	15.44	23.48
	$\bar{R}^2$	0.33	0.72	0.21	0.29	0.13	0.69	0.80	0.62
CEX wealthy top 50	γ	25.11	34.34	30.44	10.83	36.32	25.42	32.75	28.88
	$\bar{R}^2$	0.21	0.56	0.32	0.02	0.61	0.57	0.79	0.86
CEX wealthy top 70	γ	29.57	37.86	36.23	14.64	42.36	37.77	40.06	39.24
	$\bar{R}^2$	0.35	0.85	0.61	0.02	0.77	0.60	0.90	0.78

Table IA5. **State Variables and Variance Decomposition**

Table IA5 presents variable names followed by a description. The variance decomposition is defined as $\beta_z \frac{cov(x,z)}{var(x)}$ in percentage terms where β_z is a OLS coefficient for a variable z from a multiple regression of x on 160 variables where $x = F_{2,t}$, $F_{6,t}$, and $F_{8,t}$ and z is one of 160 variables. The column tcode denotes the following data transformation for a series z before estimating factors: (1) no transformation; (2) Δz_t; (3) $\Delta^2 z_t$; (4) $log(z_t)$; (5) $\Delta log(z_t)$; (6) $\Delta^2 log(z_t)$; (7) $\Delta(z_t/z_{t-1} - 1)$. In Group 9, 'JLN2015' denotes Jurado, Ludvigson, and Ng (2015), and 'BBD2016' denotes Baker, Bloom, and Davis (2016).

	Variables	Description	Variance Decomposition (%)			tcode
			$F_{2,t}$	$F_{6,t}$	$F_{8,t}$	
Group 1: Output and Income						
1	RPI	Real Personal Income	0.110	0.095	0.302	5
2	W875RX1	Real personal income ex transfer receipts	0.055	0.057	0.319	5
3	INDPRO	IP Index	0.013	2.107	-0.054	5
4	IPFPNSS	IP: Final Products and Nonindustrial Supplies	0.024	2.899	0.086	5
5	IPFINAL	IP: Final Products (Market Group)	0.035	3.298	0.092	5
6	IPCONGD	IP: Consumer Goods	0.011	2.987	0.225	5
7	IPDCONGD	IP: Durable Consumer Goods	-0.004	2.831	0.098	5
8	IPNCONGD	IP: Nondurable Consumer Goods	0.030	1.002	1.191	5
9	IPBUSEQ	IP: Business Equipment	0.030	1.659	-0.034	5
10	IPMAT	IP: Materials	0.003	0.960	-0.151	5
11	IPDMAT	IP: Durable Materials	0.001	1.398	0.072	5
12	IPNMAT	IP: Nondurable Materials	0.005	0.255	0.128	5
13	IPMANSICS	IP: Manufacturing (SIC)	0.006	2.373	-0.005	5
14	IPB51222S	IP: Residential Utilities	0.023	-0.008	1.060	5
15	IPFUELS	IP: Fuels	0.013	0.132	-0.013	5
16	CUMFNS	Capacity Utilization: Manufacturing	0.002	2.356	-0.100	2
Group 2: Labor Market						
17	HWI	Help-Wanted Index for United States	0.165	0.007	-0.047	2
18	HWIURATIO	Ratio of Help Wanted/No. Unemployed	0.196	0.007	-0.080	2
19	CLF16OV	Civilian Labor Force	0.062	0.040	-0.187	5
20	CE16OV	Civilian Employment	0.035	-0.022	-0.004	5
21	UNRATE	Civilian Unemployment Rate	0.003	0.038	-0.256	2
22	UEMPMEAN	Average Duration of Unemployment (Weeks)	-0.002	0.222	0.035	2
23	UEMPLT5	Civilians Unemployed - Less Than 5 Weeks	-0.008	0.074	0.066	5
24	UEMP5TO14	Civilians Unemployed for 5-14 Weeks	0.079	0.023	-0.006	5
25	UEMP15OV	Civilians Unemployed - 15 Weeks & Over	0.005	0.020	-0.138	5
26	UEMP15T26	Civilians Unemployed for 15-26 Weeks	0.001	0.110	-0.003	5
27	UEMP27OV	Civilians Unemployed for 27 Weeks and Over	0.005	0.240	-0.108	5
28	CLAIMSx	Initial Claims	0.067	0.139	-0.102	5
29	PAYEMS	All Employees: Total nonfarm	-0.004	-0.207	1.092	5
30	USGOOD	All Employees: Goods-Producing Industries	0.001	-0.205	0.124	5
31	CES1021000001	All Employees: Mining and Logging: Mining	0.051	0.010	-0.011	5
32	USCONS	All Employees: Construction	0.003	-0.142	-0.077	5
33	MANEMP	All Employees: Manufacturing	0.003	-0.099	0.687	5
34	DMANEMP	All Employees: Durable goods	0.010	-0.036	0.248	5
35	NDMANEMP	All Employees: Nondurable goods	-0.008	-0.113	3.316	5
36	SRVPRD	All Employees: Service-Providing Industries	-0.007	-0.113	2.305	5
37	USTPU	All Employees: Trade, Transportation & Utilities	-0.008	-0.066	1.589	5
38	USWTRADE	All Employees: Wholesale Trade	-0.010	0.141	0.773	5
39	USTRADE	All Employees: Retail Trade	-0.001	-0.043	1.641	5
40	USFIRE	All Employees: Financial Activities	-0.014	-0.037	0.769	5
41	USGOVT	All Employees: Government	0.036	-0.006	1.000	5
42	CES0600000007	Avg Weekly Hours : Goods-Producing	0.002	0.496	-2.243	1
43	AWOTMAN	Avg Weekly Overtime Hours : Manufacturing	0.000	0.193	-0.125	2
44	AWHMAN	Avg Weekly Hours : Manufacturing	0.001	0.535	-2.445	1
45	CES0600000008	Avg Hourly Earnings : Goods-Producing	-0.012	0.103	0.351	6
46	CES2000000008	Avg Hourly Earnings : Construction	-0.002	0.078	0.007	6
47	CES3000000008	Avg Hourly Earnings : Manufacturing	-0.007	0.211	0.428	6

Table IA5 – continued from previous page

	Variables	Description	Variance Decomposition (%)			tcode
			$F_{2,t}$	$F_{6,t}$	$F_{8,t}$	
Group 3: Consumption and Orders						
48	HOUST	Housing Starts: Total New Privately Owned	0.088	-0.029	4.013	4
49	HOUSTNE	Housing Starts, Northeast	0.073	-0.092	-2.602	4
50	HOUSTMW	Housing Starts, Midwest	0.037	0.002	-0.472	4
51	HOUSTS	Housing Starts, South	0.086	-0.056	8.203	4
52	HOUSTW	Housing Starts, West	0.061	0.034	5.170	4
53	PERMIT	New Private Housing Permits (SAAR)	0.065	0.063	8.062	4
54	PERMITNE	New Private Housing Permits, Northeast (SAAR)	0.068	-0.031	-1.870	4
55	PERMITMW	New Private Housing Permits, Midwest (SAAR)	0.032	0.055	1.511	4
56	PERMITS	New Private Housing Permits, South (SAAR)	0.040	0.043	11.610	4
57	PERMITW	New Private Housing Permits, West (SAAR)	0.054	0.063	6.352	4
Group 4: Orders and Inventories						
58	DPCERA3M086SBEA	Real personal consumption expenditures	0.115	0.026	0.157	5
59	CMRMTSPLx	Real Manu. and Trade Industries Sales	0.096	0.643	0.061	5
60	RETAILx	Retail and Food Services Sales	0.089	0.169	0.082	5
61	ACOGNO	New Orders for Consumer Goods	-0.030	-0.062	2.080	5
62	AMDMNOx	New Orders for Durable Goods	-0.004	1.182	0.241	5
63	ANDENOx	New Orders for Nondefense Capital Goods	0.019	0.819	0.084	5
64	AMDMUOx	Unfilled Orders for Durable Goods	0.072	-0.001	0.130	5
65	BUSINVx	Total Business Inventories	0.108	0.017	0.068	5
66	ISRATIOx	Total Business: Inventories to Sales Ratio	0.142	1.062	0.229	2
67	UMCSENTx	Consumer Sentiment Index	0.330	1.493	4.243	2
Group 5: Money and Credit						
68	M1SL	M1 Money Stock	-0.006	0.271	0.015	6
69	M2SL	M2 Money Stock	0.003	1.192	-0.034	6
70	M2REAL	Real M2 Money Stock	-0.038	0.293	-0.167	5
71	BOGMBASE	Monetary Base; Total	0.000	0.021	0.127	6
72	TOTRESNS	Total Reserves of Depository Institutions	0.013	0.049	0.351	6
73	NONBORRES	Reserves Of Depository Institutions	0.010	0.171	0.248	7
74	BUSLOANS	Commercial and Industrial Loans	0.022	-0.013	0.094	6
75	REALLN	Real Estate Loans at All Commercial Banks	-0.017	-0.020	0.000	6
76	NONREVSL	Total Nonrevolving Credit	0.003	-0.016	0.026	6
77	CONSPI	Nonrevolving consumer credit to Personal Income	0.007	0.340	0.114	2
78	MZMSL	MZM Money Stock	0.007	1.502	-0.066	6
79	DTCOLNVHFNM	Consumer Motor Vehicle Loans Outstanding	0.050	0.014	0.119	6
80	DTCTHFNM	Total Consumer Loans and Leases Outstanding	0.034	0.004	0.046	6
81	INVEST	Securities in Bank Credit at All Commercial Banks	-0.003	0.094	0.007	6
Group 6: Prices						
82	WPSFD49207	PPI by Commodity: Final Demand: Finished Goods	0.008	0.185	0.233	6
83	WPSFD49502	PPI by Commodity: Final Demand: Personal Consumption Goods	0.012	0.195	0.245	6
84	WPSID61	PPI by Commodity: Intermediate Demand, Processed Goods	0.023	0.329	-0.017	6
85	WPSID62	PPI by Commodity: Intermediate Demand, Unprocessed Goods	0.010	0.443	-0.038	6
86	OILPRICEx	Crude Oil, spliced WTI and Cushing	0.021	0.001	0.049	6
87	PPICMM	PPI: Metals and metal products	0.064	0.077	0.083	6
88	CPIAUCSL	CPI : All Items	-0.007	0.339	0.111	6
89	CPIAPPSL	CPI : Apparel	0.006	0.003	0.001	6
90	CPITRNSL	CPI : Transportation	0.059	0.353	0.196	6
91	CPIMEDSL	CPI : Medical Care	0.000	-0.025	0.011	6
92	CUSR0000SAC	CPI : Commodities	0.011	0.421	0.249	6
93	CUSR0000SAD	CPI : Durables	0.016	-0.007	0.011	6
94	CUSR0000SAS	CPI : Services	0.015	0.001	0.084	6
95	CPIULFSL	CPI : All Items Less Food	0.029	0.308	0.062	6
96	CUSR0000SA0L2	CPI : All items less shelter	-0.002	0.415	0.109	6

Table IA5 – continued from previous page

	Variables	Description	Variance Decomposition (%)			tcode
			$F_{2,t}$	$F_{6,t}$	$F_{8,t}$	
97	CUSR0000SA0L5	CPI : All items less medical care	0.003	0.385	0.091	6
98	PCEPI	Personal Cons. Expend.: Chain Index	0.008	0.260	0.125	6
99	DDURRG3M086SBEA	Personal Cons. Exp: Durable goods	-0.002	0.009	-0.010	6
100	DNDGRG3M086SBEA	Personal Cons. Exp: Nondurable goods	0.009	0.444	0.243	6
101	DSERRG3M086SBEA	Personal Cons. Exp: Services	0.002	0.000	-0.001	6
Group 7: Interest rate and Exchange Rates						
102	FEDFUNDS	Effective Federal Funds Rate	0.110	0.778	-0.113	2
103	CP3Mx	3-Month AA Financial Commercial Paper Rate	0.202	1.460	-0.146	2
104	TB3MS	3-Month Treasury Bill	0.073	2.529	-0.202	2
105	TB6MS	6-Month Treasury Bill	0.133	2.844	-0.216	2
106	GS1	1-Year Treasury Rate	0.115	3.301	-0.232	2
107	GS5	5-Year Treasury Rate	-0.018	5.466	-0.130	2
108	GS10	10-Year Treasury Rate	-0.055	5.148	0.002	2
109	AAA	Moody's Seasoned Aaa Corporate Bond Yield	0.235	3.526	0.064	2
110	BAA	Moody's Seasoned Baa Corporate Bond Yield	0.559	3.263	0.038	2
111	COMPAPFFx	3-Month Commercial Paper Minus FEDFUNDS	-0.010	0.583	0.774	1
112	TB3SMFFM	3-Month Treasury C Minus FEDFUNDS	0.031	0.507	0.267	1
113	TB6SMFFM	6-Month Treasury C Minus FEDFUNDS	0.004	0.646	0.382	1
114	T1YFFM	1-Year Treasury C Minus FEDFUNDS	-0.015	0.755	0.359	1
115	T5YFFM	5-Year Treasury C Minus FEDFUNDS	0.071	0.135	0.076	1
116	T10YFFM	10-Year Treasury C Minus FEDFUNDS	0.133	0.046	-0.338	1
117	AAAFFM	Moody's Aaa Corporate Bond Minus FEDFUNDS	0.114	-0.010	-0.964	1
118	BAAFFM	Moody's Baa Corporate Bond Minus FEDFUNDS	0.110	0.018	-0.898	1
119	TWEXAFEGSMTHx	Trade Weighted U.S. Dollar Index: Major Currencies	0.315	1.771	8.964	5
120	EXSZUSx	Switzerland / U.S. Foreign Exchange Rate	0.054	2.467	2.770	5
121	EXJPUSx	Japan / U.S. Foreign Exchange Rate	0.013	2.247	2.117	5
122	EXUSUKx	U.S. / U.K. Foreign Exchange Rate	0.092	0.621	2.653	5
123	EXCAUSx	Canada / U.S. Foreign Exchange Rate	0.846	0.035	2.019	5
124	RREL	Relative T-bill rate	0.028	1.023	-0.047	1
Group 8: Stock Market						
125	S&P 500	S&P's Common Stock Price Index: Composite	4.368	0.379	0.037	5
126	S&P: indust	S&P's Common Stock Price Index: Industrials	4.144	0.422	0.018	5
127	S&P div yield	S&P's Composite Common Stock: Dividend Yield	2.360	-0.024	0.017	2
128	S&P PE ratio	S&P's Composite Common Stock: Price-Earnings Ratio	3.117	0.058	0.021	5
129	VXOCLSx	CBOE S&P 100 Volatility Index: VXO	0.659	2.463	3.685	1
130	DE	Dividend payout ratio	0.072	0.163	0.212	1
131	SVAR	Stock variance	0.911	1.992	4.443	1
132	NoDur	Consumer Nondurables	3.884	0.152	0.054	1
133	Durbl	Consumer Durables	5.175	0.494	0.068	1
134	Manuf	Manufacturing	5.682	0.493	0.386	1
135	Enrgy	Oil, Gas, and Coal Extraction and Products	3.076	0.129	0.477	1
136	HiTec	Business Equipment	5.064	0.843	0.123	1
137	Telcm	Telephone and Television Transmission	4.504	0.102	0.040	1
138	Shops	Wholesale, Retail, and Some Services	4.630	0.380	0.020	1
139	Hlth	Healthcare, Medical Equipment, and Drugs	3.069	0.370	0.124	1
140	Utils	Utilities	2.129	-0.051	0.026	1
141	Other	Other	5.647	0.477	0.093	1
142	SMALLLoBM	Small and Value	5.134	0.754	0.035	1
143	ME1BM2	Small and Neutral	5.612	0.527	0.041	1
144	SMALLHiBM	Small and Growth	5.396	0.458	0.010	1
145	BIGLoBM	Big and Value	5.753	0.594	0.203	1
146	ME2BM2	Big and Neutral	6.208	0.309	0.216	1
147	BIGHiBM	Big and Growth	5.690	0.475	0.098	1
Group 9: Economic uncertainty						
148	JLN-fin-1	1-month Financial uncertainty by JLN 2015	0.413	1.805	1.422	1
149	JLN-fin-3	3-month Financial uncertainty by JLN 2015	0.396	1.869	1.523	1
150	JLN-fin-12	12-month Financial uncertainty by JLN2015	0.351	2.021	1.952	1
151	JLN-mac-1	1-month Macro uncertainty by JLN2015	0.107	0.417	0.546	1

Table IA5 – continued from previous page

	Variables	Description	Variance Decomposition (%)			tcode
			$F_{2,t}$	$F_{6,t}$	$F_{8,t}$	
152	JLN-mac-3	3-month Macro uncertainty by JLN2015	0.108	0.402	0.758	1
153	JLN-mac-12	12-month Macro uncertainty by JLN2015	0.091	0.292	1.290	1
154	JLN-real-1	1-month Real uncertainty by JLN2015	0.046	0.223	0.223	1
155	JLN-real-3	3-month Real uncertainty by JLN2015	0.051	0.214	-0.077	1
156	JLN-real-12	12-month Real uncertainty by JLN2015	0.063	0.108	-0.156	1
157	log-EPU	Economic Policy Uncertainty by BBD2016	0.035	2.040	0.487	1
Group 10: Financial etc.						
158	BM	Book-to-market ratio	-0.005	-0.081	1.774	1
159	NTIS	Net equity expansion	0.021	0.093	0.903	1
160	Surplus3m	3-month surplus ratio by Duffee (2005)	-0.004	0.039	-0.178	1

Table IA6. **Descriptive Statistics of the Long-Run Risk Measure Using VAR**

This table reports the number of observations, mean, standard deviation, and percentiles of the demeaned long-run consumption risk measure using the VAR and its component. The long-run risk is measured by $(\hat{E}_{t+1} - \hat{E}_t)\sum_{s=0}^{\infty}\beta^s(c_{t+s+1} - c_{t+s}) = \epsilon^{SR}_{t+1} + \epsilon^{LR}_{t+1}$ where $c_{t+1} - c_t = \mu_c + U_c x_t + \epsilon^{SR}_{t+1}$, $x_{t+1} = Gx_t + \epsilon^{x}_{t+1}$, and $\epsilon^{LR}_{t+1} = \delta U_c(I - \delta G)^{-1}\epsilon^{x}_{t+1}$, following Hansen et al. (2007) and Hansen, Heaton, and Li (2008). Time period spans from March 1984 to December 2019.

	N	Average (%)	Std. (%)	Percentiles (%) 1st	5th	25th	50th	75th	95th	99th
$(\hat{E}_{t+1} - \hat{E}_t)\sum_{s=0}^{\infty}\beta^s(c_{t+s+1} - c_{t+s})$	430	0.00	8.19	-21.82	-13.36	-5.15	0.21	5.58	13.38	19.44
ϵ^{SR}_{t+1}	430	0.00	8.24	-17.93	-13.40	-5.59	-0.05	5.54	14.37	21.03
ϵ^{LR}_{t+1}	430	0.00	3.09	-9.39	-4.78	-1.79	0.09	1.83	5.06	7.61

Table IA7. **Summary Statistics of Corporate Bond Database**

This table reports the summary statistics of monthly bond returns in percentage form in our corporate bond database. The sample period is from February 1973 to December 2019.

	N	Average	Std.	Percentiles								
Data				1	5	10	25	50	75	90	95	99
All	2,297,675	0.85	7.39	-8.32	-3.50	-1.94	-0.29	0.70	1.80	3.45	5.16	11.12
Lehman Brothers	1,541,746	0.94	8.13	-7.76	-3.55	-2.01	-0.27	0.80	1.92	3.59	5.33	10.74
TRACE	589,814	0.61	4.55	-9.08	-3.21	-1.73	-0.32	0.42	1.45	3.02	4.54	11.27
NAIC	17,868	0.85	18.19	-20.55	-6.37	-3.29	-0.76	0.62	1.91	4.20	6.71	18.90
DataStream	148,247	0.76	6.14	-13.76	-3.77	-1.98	-0.23	0.67	1.73	3.57	5.66	14.33

Table IA8. **Descriptive Statistics**

This table 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 5 long-term reversal portfolios. Asset data span from February 1973 to December 2019.

				Percentiles (%)						
	N	Average (%)	Std (%)	1st	5th	25th	50th	75th	95th	99th
Test assets returns (1-month growth)										
Credit spread	5,570	0.70	2.13	-5.02	-2.37	-0.25	0.70	1.65	3.67	6.95
Downside	2,675	0.70	2.18	-5.61	-2.53	-0.15	0.62	1.53	4.04	7.58
Maturity	2,795	0.67	2.02	-4.99	-2.47	-0.23	0.63	1.56	3.62	7.01
Rating	2,795	0.68	2.14	-4.99	-2.59	-0.35	0.69	1.70	3.76	7.02
Intermediary	2,615	0.64	2.09	-5.49	-2.57	-0.28	0.61	1.52	3.63	7.50
IdioVol	2,675	0.70	2.18	-5.30	-2.40	-0.15	0.62	1.56	3.91	7.79
Reversal	2,535	0.69	2.08	-5.17	-2.30	-0.23	0.65	1.53	3.71	7.30
All portfolios	21,660	0.68	2.12	-5.18	-2.46	-0.23	0.65	1.59	3.74	7.30

Table IA9. **Cyclicality of Consumption Growth**

		Default Spread	Δ Macro Uncertainty	Corp Bond Returns	Stock Returns	Recess Dummy	Term Spread	D/P Ratio
Panel A. Wealthy Households' Consumption								
CEX LR	b_1	-0.991	-0.169	0.251	0.035	-0.005	-0.127	0.060
	$t(b_1)$	(-2.21)	(-3.48)	(3.53)	(0.94)	(-0.23)	(-0.23)	(0.12)
	R^2	0.01	0.01	0.02	0.00	0.00	0.00	0.00
Panel B. Bondholders' Consumption								
CEX LR	b_1	-2.489	-0.127	0.305	0.080	-0.033	-0.478	-1.140
	$t(b_1)$	(-4.59)	(-2.59)	(2.61)	(1.35)	(-2.72)	(-0.75)	(-2.27)
	R^2	0.06	0.01	0.02	0.01	0.02	0.01	0.02
Panel C. NIPA Consumption								
NIPA LR	b_1	-0.856	-0.119	0.125	0.064	-0.040	0.810	-0.473
	$t(b_1)$	(-0.85)	(-1.43)	(1.12)	(1.52)	(-2.13)	(1.36)	(-0.64)
	R^2	0.01	0.01	0.01	0.01	0.07	0.05	0.01
NIPA 1Q	b_1	-0.319	-0.019	0.004	0.017	-0.010	-0.058	-0.097
	$t(b_1)$	(-3.65)	(-0.82)	(0.16)	(2.20)	(-6.11)	(-1.62)	(-1.33)
	R^2	0.11	0.02	0.00	0.06	0.24	0.02	0.02

This table reports the estimates for the regression of consumption growth on macroeconomic factors

$$\sum_{s=0}^{19} \delta^s \Delta c_{t+s+1} = b_0 + b_1 x_{t+1} + u_{t+s+1},$$

where x_{t+1} is the stock and corporate bond market excess returns, a dummy variable for NBER recessions, changes in macroeconomic uncertainty of Jurado, Ludvigson, and Ng (2015), term spreads, default spreads, the dividend-price ratio of the stock market, and stock market excess returns.

Table IA10. **Estimates for Consumption Predictive Regression**

This table reports the estimates for the consumption forecasting regression:

$$c_{m+1} - c_{m-2} = \mu_c + U_c x_{m-2} + \varepsilon_{m+1},$$

where the left-hand-side variables are quarterly consumption growth (in percent) for wealthy households, bondholders and aggregate households. Panel B shows the product of the slope coefficients and standard deviation of the state variables. The values in parentheses are standard errors with the Newey-West 24-month lags.

	μ_c	U_c						
	constant	$F_{2,m-2}$	$F_{6,m-2}$	$F_{8,m-2}$	$F_{2,m-3}$	$F_{6,m-3}$	$F_{8,m-3}$	Adj.R2
Panel A. VAR Coefficient Estimates								
Wealthy Households	-0.89	-0.16	-5.07	-13.79	-2.98	-2.71	9.77	0.027
	(0.32)	(1.44)	(2.09)	(3.37)	(1.43)	(2.83)	(3.77)	
Bondholders	-1.03	0.66	-5.92	-18.55	-3.08	-0.93	13.72	0.029
	(0.39)	(1.54)	(3.01)	(4.21)	(2.10)	(3.56)	(4.21)	
NIPA Aggregate	0.45	-0.13	-0.03	-0.50	-0.13	0.09	-0.15	0.027
	(0.07)	(0.10)	(0.14)	(0.23)	(0.10)	(0.15)	(0.28)	
Panel B. Coefficient $\times$ Standard Deviation of State Variables								
Wealthy Households		-0.05	-0.83	-1.53	-0.84	-0.44	1.08	
Bondholders		0.19	-0.97	-2.06	-0.87	-0.15	1.52	
NIPA Aggregate		-0.04	-0.01	-0.05	-0.04	0.01	-0.02	

Table IA11. **Regression of Expected Consumption Growth on Asset Returns and Business Cycle Variables**

Table reports the slope coefficient, the associated t-statistics, and R-squared of the univariate regression of shocks to long-run consumption growth as well as expected consumption growth on state variables. The values in parentheses are t-statistics with the Newey-West 24-month lags.

		Corp Bond Returns	Stock Returns	Macro Uncertainty	Recess Dummy	Term Spread	Default Spread	D/P Ratio
LHV		Shocks to long-run expected growth			$E_t[c_{t+1} - c_t]$			
Wealthy Household	b	0.141	0.099	-0.107	-0.010	-0.153	-0.554	-0.363
	$t(b)$	(1.63)	(3.91)	(-1.48)	(-3.99)	(-1.92)	(-4.43)	(-3.19)
	R^2	0.01	0.02	0.01	0.06	0.03	0.09	0.07
Bondholders	b	0.070	0.077	-0.056	-0.008	-0.154	-0.461	-0.371
	$t(b)$	(0.63)	(1.72)	(-0.71)	(-3.12)	(-1.92)	(-3.91)	(-3.66)
	R^2	0.00	0.01	0.00	0.04	0.03	0.07	0.08
NIPA Aggregate	b	0.006	0.017	-0.014	0.000	-0.003	-0.025	-0.031
	$t(b)$	(0.40)	(3.13)	(-0.90)	(-0.94)	(-0.36)	(-1.49)	(-2.50)
	R^2	0.00	0.08	0.01	0.01	0.00	0.03	0.08

Table IA12. **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 IA13. **Descriptive Statistics of SCF Asset Holders**

This table presents the descriptive statistics of non-corporate bondholders (Panel A), corporate bondholders (Panel B), non-equityholders (Panel C), equityholders that account for indirect holdings through retirement accounts (Panel D), and total respondents (Panel E) in the Survey of Consumer Finances (SCF) are from 1992, 1995, 1998, 2001, 2004, 2007, 2010, 2013, 2016, and 2019 waves. Corporate bond holders are defined as respondents who directly or indirectly hold corporate bonds through funds. Wealth is the value of checking, savings, mutual funds, stocks, and bonds. Income is the total household 12-month income before taxes. Dividend income is the total family annual dividend income. All dollar values are in 2019 dollars.

	Equity	Corporate bonds	Wealth	Income	Dividend	Age	High	College	Nonwhite	# of kids	Married	Male
				Panel A: Non-corporate bondholders								
Mean	110,099.00	0.00	158,026.10	88,892.10	937.22	49.85	0.39	0.55	0.28	0.81	0.58	0.72
Median	10.00	0.00	8,477.37	53,895.91	0.00	48.00	0.00	1.00	0.00	0.00	1.00	1.00
				Panel B: Corporate bondholders								
Mean	1,186,158.00	187,377.00	2,094,333.00	309,973.50	14,008.09	59.48	0.15	0.85	0.07	0.53	0.70	0.81
Median	296,242.40	31,180.71	589,877.80	128,251.20	2,000.00	60.00	0.00	1.00	0.00	0.00	1.00	1.00
				Panel C: Non-equityholders								
Mean	0.00	156.39	8,070.34	44,982.79	50.72	50.03	0.50	0.40	0.37	0.79	0.47	0.64
Median	0.00	0.00	1,084.55	32,579.77	0.00	48.00	0.00	0.00	0.00	0.00	0.00	1.00
				Panel D: Equityholders								
Mean	258,596.20	7,226.72	378,813.50	139,923.10	2,306.39	50.05	0.28	0.71	0.18	0.82	0.69	0.80
Median	35,141.45	0.00	55,305.77	86,320.40	0.00	49.00	0.00	1.00	0.00	0.00	1.00	1.00
				Panel E: Total respondents								
Mean	131,671.20	3,756.44	196,844.20	93,324.23	1,199.26	50.04	0.39	0.56	0.27	0.81	0.58	0.72
Median	176.74	0.00	9,051.93	54,941.79	0.00	49.00	0.00	1.00	0.00	0.00	1.00	1.00

Table IA14. **Probit regression of Corporate bond ownership Using Survey of Consumer Finances**

This table reports the Probit regression of households' corporate bond ownership on households characteristics that are available in both Survey of Consumer Finances(SCF) and Consumption Expenditure (CEX). The SCF data are from the 1992, 1995, 1998, 2001, 2004, 2007, 2010, 2013, 2016, and 2019 waves. The dependent variable is a dummy variable that takes one if a household has a positive holding either in corporate bonds (SCF variable code X7634) or funds/ETFs that invest in corporate bonds (SCF variable code X3827) otherwise zero. The regressors are the age of household (*age*), age squared (*age*^{2}), *highschool* indicator for households whose highest education is high school (educ>=4 and educ=<8), an *college* indicator for households whose education level is higher than high school (educ>=9), an indicator for race not being white/Caucasian (race=1), the number of children (*Kids*), log of one plus the ratio of financial wealth to labor income where financial wealth equals the value of checking, savings, mutual funds, stocks, and bonds and labor income is total household 12-month income before taxes (*Log(1+Wealth/Income)*), and log of one plus the ratio of dividend income (SCF variable code X5710) to labor income (*Log(1+Div/Income)*).The SCF data are from the 1992, 1995, 1998, 2001, 2004, 2007, 2010, 2013, 2016, and 2019 waves. Standard errors are clustered by the wave.

	Coeff.	Std. error
age	0.048***	0.006
age^2	-3.4$\times 10^{-4}$***	5.4$\times 10^{-5}$
$1_{i \in highschool}$	0.237**	0.114
$1_{i \in college}$	0.781***	0.122
$1_{i \in nonwhite}$	-0.272***	0.040
Kids	0.019	0.012
$1_{i \in married}$	0.254***	0.031
$1_{i \in male}$	0.050	0.050
$1_{i \in 1992}$	0.486***	0.010
$1_{i \in 1995}$	0.287***	0.007
$1_{i \in 1998}$	0.236***	0.007
$1_{i \in 2001}$	0.150***	0.005
$1_{i \in 2004}$	0.267***	0.004
$1_{i \in 2007}$	0.057***	0.002
$1_{i \in 2010}$	0.134***	0.005
$1_{i \in 2013}$	0.112***	0.004
$1_{i \in 2016}$	-0.024***	0.001
Log(1+Wealth/Income)	0.600***	0.019
Log(1+Div/Income)	-0.848***	0.084
Cons	-4.678***	0.311
Number of Obs.	50,410	
Pseudo R^2	0.2616	

Table IA15. **GMM Cross-Sectional Regression Using the Reverse Regression**

This table reports GMM cross-sectional regression results over different long-run horizons S using the reverse regression: $c\hat{o}v(\sum_{s=0}^{S-1}\delta^s(c_{t+1+s}-c_{t+s}), r_{i,t+1}-r_{f,t}) = \eta + \frac{1}{(\gamma-1)}(\hat{E}[r_{i,t+1}-r_{f,t}] + \frac{\hat{\sigma}^2(r_{i,t+1})}{2} - \frac{\hat{\sigma}^2(r_{f,t})}{2}) + u_i$ where $r_{i,t+1}$ is the quarterly log return of an asset i, $r_{f,t}$ is the quarterly log rate of 30-day T-bill, $\delta = 0.95^{1/4}$, c_t is the log consumption. The long-run consumption risk factor is measured by the discounted cumulative consumption growth over multiple horizons $\sum_{s=0}^{S-1}\delta^s(c_{t+1+s}-c_{t+s})$. The quantity of risk is jointly estimated with parameters ζ, η, and γ using GMM. Test assets are 40 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 5 long-term reversal 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 March 1984 to December 2019. Unconditional pricing errors ζ and η are multiplied by 100 for ease of exposition.

S (quarters)	1	2	4	8	12	16	20	24
η (%)	0.00	-0.01	0.01	-0.01	0.01	-0.01	-0.03	-0.01
	[-0.02 0.02]	[-0.03 0.02]	[-0.02 0.02]	[-0.02 0.01]	[-0.01 0.03]	[-0.03 0.02]	[-0.05 0.01]	[-0.03 0.02]
γ	70.6	32.2	78.8	73.5	127.6	22.8	19.0	37.6
	[32.1 5×10^{14}]	[16.9 3×10^{10}]	[32.0 2×10^{15}]	[35.2 3×10^{15}]	[41.8 4×10^{15}]	[16.1 85.8]	[14.0 54.5]	[25.7 119.7]
$\bar{R}^2$	0.32	0.72	0.21	0.29	0.12	0.69	0.80	0.61
	[0 0.66]	[0 0.93]	[0 0.75]	[0 0.66]	[0 0.54]	[0.04 0.9]	[0.26 0.9]	[0.08 0.8]
$\frac{RMSE}{RMSR}$	0.30	0.19	0.38	0.57	0.41	0.21	0.23	0.30
Number of assets	40	40	40	40	40	40	40	40
Number of asset-month	16,940	16,820	16,580	16,100	15,620	15,140	14,660	14,180

Table IA16. **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 $\sum_{s=0}^{19} \delta^s (c_{t+1+s} - c_{t+s})$ where $r_{i,t+1}$ is the quarterly log return of an asset i, $r_{f,t}$ is the quarterly log rate of 30-day T-bill, $\delta = 0.95^{1/4}$, and c_t is the log consumption. The long-run consumption risk factor is measured by the discounted cumulative 20-quarter consumption growth. Consumption of wealthy households defined as the top 30% of asset holders from CEX data is used. In the second-stage cross-sectional regression, average one month ahead excess returns $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\hat{\sigma}^2(r_{i,t+1})}{2} - \frac{\hat{\sigma}^2(r_{f,t})}{2}$ are regressed on estimated betas $\hat{\beta}_i$ cross-sectionally. Test assets are 40 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 5 long-term reversal portfolios. Reported are the intercepts λ_0 and the price of risk λ_1 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 $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N} E(R_i^e)^2}$. '$\bar{R}^2$ with same λ_1' and '$\frac{RMSE}{RMSR}$ with same λ_1' report the pricing performance by imposing γ estimated using all portfolios. Time period spans from March 1984 to December 2019. Unconditional pricing errors λ_0 are multiplied by 100 for ease of exposition.

Assets	Credit Spread portfolios	Downside portfolios	Maturity portfolios	Rating portfolios	Intermediary portfolios	IdioVol portfolios	Reversal portfolios	All portfolios
λ_0 (%)	0.75	0.64	0.20	0.82	0.66	0.72	0.81	0.74
	[0.33 1]	[-0.01 0.85]	[-0.46 1.28]	[0.14 1.17]	[0.21 1.55]	[0.1 0.94]	[0.47 1.13]	[0.42 0.96]
λ_1	0.12	0.13	0.27	0.10	0.11	0.11	0.09	0.11
	[0.06 0.23]	[0.04 0.31]	[-0.13 0.52]	[-0.02 0.29]	[-0.15 0.21]	[0.03 0.29]	[0.04 0.14]	[0.05 0.19]
$\bar{R}^2$	0.94	0.96	0.56	0.96	0.25	0.87	0.69	0.80
	[0.36 0.98]	[0.68 1]	[0.01 0.96]	[0.06 0.99]	[0 0.88]	[0.45 0.99]	[0.3 0.94]	[0.26 0.9]
$\bar{R}^2$ with same λ_1	0.93	0.95	0.37	0.96	0.25	0.87	0.66	0.80
$\frac{RMSE}{RMSR}$	0.08	0.06	0.12	0.03	0.15	0.10	0.16	0.12
$\frac{RMSE}{RMSR}$ with same λ_1	0.09	0.07	0.14	0.05	0.18	0.10	0.17	0.12
Number of assets	10	5	5	5	5	5	5	40
Number of asset-month	3,690	1,845	1,845	1,845	1,785	1,845	1,805	14,660

Table IA17. **Two-Pass Regression Based on VAR**

This table presents the cross-sectional test results using the long-run risk measure based on VAR. In this table, The long-run consumption risk factor is measured as $(\hat{E}_{t+1} - \hat{E}_t)\sum_{s=0}^{\infty}\delta^s(c_{t+1+s} - c_{t+s})$. A two-pass regression is run where average excess returns are regressed on estimated betas cross-sectionally. Consumption of wealthy households defined as the top 30% of asset holders from CEX data is used. 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 5 long-term reversal 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 $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N}E(R_i^e)^2}$. '$\bar{R}^2$ with same λ_1' and '$\frac{RMSE}{RMSR}$ with same λ_1' report the pricing performance by imposing λ_1 estimated using all portfolios. Time period spans from March 1984 to December 2019. Unconditional pricing errors λ_0 are multiplied by 100 for ease of exposition.

Assets	Credit Spread portfolios	Downside portfolios	Maturity portfolios	Rating portfolios	Intermediary portfolios	IdioVol portfolios	Reversal portfolios	All portfolios
λ_0 (%)	0.76	0.53	0.68	0.90	0.58	0.71	0.64	0.74
	[0.28 1.23]	[-0.07 0.83]	[0.17 1.34]	[0.32 1.58]	[0.38 1.19]	[0.00 0.94]	[0.29 1.04]	[0.40 1.00]
λ_1	0.12	0.16	0.16	0.09	0.19	0.11	0.16	0.12
	[-0.02 0.31]	[0.04 0.46]	[-0.13 0.49]	[-0.18 0.39]	[-0.11 0.27]	[0.03 0.47]	[0.06 0.26]	[0.04 0.27]
$\bar{R}^2$	0.96	0.99	0.26	0.88	0.89	0.91	0.66	0.84
	[0.06 0.98]	[0.25 1.00]	[0.00 0.98]	[0.03 0.97]	[0.00 0.97]	[0.31 1.00]	[0.14 0.92]	[0.15 0.89]
$\bar{R}^2$ with same λ_1	0.96	0.94	0.25	0.72	0.78	0.90	0.62	0.84
$\frac{RMSE}{RMSR}$	0.06	0.04	0.16	0.05	0.06	0.09	0.15	0.11
$\frac{RMSE}{RMSR}$ with same λ_1	0.06	0.09	0.17	0.08	0.08	0.11	0.17	0.11
Number of assets	10	5	5	5	5	5	5	40
Number of asset-month	4,260	2,130	2,130	2,130	2,070	2,130	2,090	16,940

Table IA18. **Two-Pass Regression Using NIPA Aggregate Consumption**

This table reports two-pass regression results using NIPA aggregate consumption. 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 $\sum_{s=0}^{19} \delta^s (c_{t+1+s} - c_{t+s})$ 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 factor is measured by the discounted cumulative 24-month consumption growth. 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 40 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 5 long-term reversal portfolios. Reported are the intercepts λ_0 and the price of risk λ_1 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 $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N} E(R_i^e)^2}$. '$\bar{R}^2$ with same λ_1' and '$\frac{RMSE}{RMSR}$ with same λ_1' report the pricing performance by imposing γ estimated using all portfolios. Time period spans from February 1973 to December 2019. Unconditional pricing errors λ_0 are multiplied by 100 for ease of exposition.

Assets	Credit Spread portfolios	Downside portfolios	Maturity portfolios	Rating portfolios	Intermediary portfolios	IdioVol portfolios	Reversal portfolios	All portfolios
λ_0 (%)	0.17	0.02	0.52	0.23	0.17	0.16	0.09	0.26
	[-1.22 0.99]	[-0.71 0.99]	[0.33 1.13]	[-1.48 1.04]	[-0.43 1.14]	[-0.3 1.02]	[-0.75 1.3]	[-0.19 1.02]
λ_1	0.02	0.03	0.01	0.02	0.02	0.03	0.04	0.02
	[0.01 0.04]	[0.01 0.05]	[0 0.02]	[0.01 0.03]	[-0.01 0.04]	[0.01 0.05]	[-0.01 0.05]	[0.01 0.03]
$\bar{R}^2$	0.86	0.97	0.44	0.96	0.98	0.98	0.45	0.64
	[0.48 0.94]	[0.4 1]	[0 0.74]	[0.74 0.98]	[0.01 0.98]	[0.36 0.99]	[0 0.86]	[0.08 0.79]
$\bar{R}^2$ with same λ_1	0.84	0.88	-0.27	0.91	0.98	0.93	0.37	0.64
$\frac{RMSE}{RMSR}$	0.15	0.05	0.10	0.05	0.03	0.04	0.22	0.20
$\frac{RMSE}{RMSR}$ with same λ_1	0.17	0.13	0.23	0.21	0.16	0.11	0.33	0.20
Number of assets	10	5	5	5	5	5	5	40
Number of asset-month	5,300	2,540	2,660	2,660	2,480	2,540	2,380	20,560

Table IA19. **Selection of Factors and Lag for Consumption Predictability**

Table IA19 shows the state vector which minimizes the AIC along with some of other 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 160 macro and financial variables. $F_{n,t}$ is the *n*-th factor from the PCA based on 160 pre-selected variables.

x_t	The number of lags	R^2	Adj.R^2	AIC
$F_{1,t}$	0	0.0018	-0.0005	-4.9829
$F_{1,t}$	1	0.0025	-0.0022	-4.9789
$F_{1,t}$	2	0.0026	-0.0045	-4.9744
...				
$F_{1,t}$, $F_{2,t}$, $F_{3,t}$	0	0.0074	0.0004	-4.9792
$F_{1,t}$, $F_{2,t}$, $F_{3,t}$	1	0.0183	0.0043	-4.9763
$F_{1,t}$, $F_{2,t}$, $F_{3,t}$	2	0.0241	0.0032	-4.9682
...				
$F_{2,t}$, $F_{6,t}$, $F_{8,t}$	0	0.0186	0.0117	-4.9906
$\boldsymbol{F_{2,t}}$, $\boldsymbol{F_{6,t}}$, $\boldsymbol{F_{8,t}}$	**1**	**0.0410**	**0.0275**	**-4.9998**
$F_{2,t}$, $F_{6,t}$, $F_{8,t}$	2	0.0420	0.0214	-4.9867
...				
$F_{1,t}$, $F_{2,t}$, ... ,$F_{8,t}$	0	0.0311	0.0127	-4.9802
$F_{1,t}$, $F_{2,t}$, ... ,$F_{8,t}$	1	0.0699	0.0339	-4.9838
$F_{1,t}$, $F_{2,t}$, ... ,$F_{8,t}$	2	0.0806	0.0261	-4.9581

Table IA20. **Tests Using the Long-Run Risk Measure Based on VAR, Accounting For Volatility Shock**

This table presents GMM cross-sectional test results using the long-run risk measure based on VAR. The long-run consumption risk factor is measured as $(\hat{E}_{t+1} - \hat{E}_t) \sum_{s=0}^{\infty} \delta^s (c_{t+1+s} - c_{t+s})$. The quantity of risk is jointly estimated with parameters ζ and γ using GMM. Consumption of wealthy households defined as the top 30% of asset holders from CEX data is used. 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 5 long-term reversal 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 $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N} E(R_i^e)^2}$. '$\bar{R}^2$ with same γ' and '$\frac{RMSE}{RMSR}$ with same γ' report the pricing performance by imposing γ estimated using all portfolios. Time period spans from March 1984 to December 2019. 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	LT Reversal portfolios	All portfolios
ζ (%)	0.64	0.48	0.74	0.83	0.42	0.67	0.39	0.65
	[0.05 1.1]	[0.06 0.81]	[0.34 0.98]	[0.17 1.21]	[-0.14 1.07]	[0.16 0.96]	[-0.29 1.2]	[0.21 1]
γ	20.94	22.14	-18.00	17.24	26.00	18.70	25.85	20.62
	[-14.37 30.61]	[-27.84 31.52]	[-22.69 28.05]	[-1.81 29.66]	[-24.14 34.83]	[-25.05 30.32]	[7.24 34.33]	[1.26 28.81]
$\bar{R}^2$	0.97	0.99	1.00	0.89	0.72	0.94	0.51	0.85
	[0.06 0.99]	[0.68 1.00]	[0.75 1.00]	[0.01 0.97]	[0.00 0.98]	[0.47 0.99]	[0.10 0.79]	[0.21 0.92]
$\bar{R}^2$ with same γ	0.97	0.98	0.69	0.80	0.63	0.91	0.47	0.85
$\frac{RMSE}{RMSR}$	0.06	0.03	0.01	0.05	0.09	0.07	0.18	0.11
$\frac{RMSE}{RMSR}$ with same γ	0.06	0.07	0.11	0.07	0.11	0.11	0.19	0.11
Number of assets	10	5	5	5	5	5	5	40
Number of asset-month	4260	2130	2130	2130	2070	2130	2090	16940

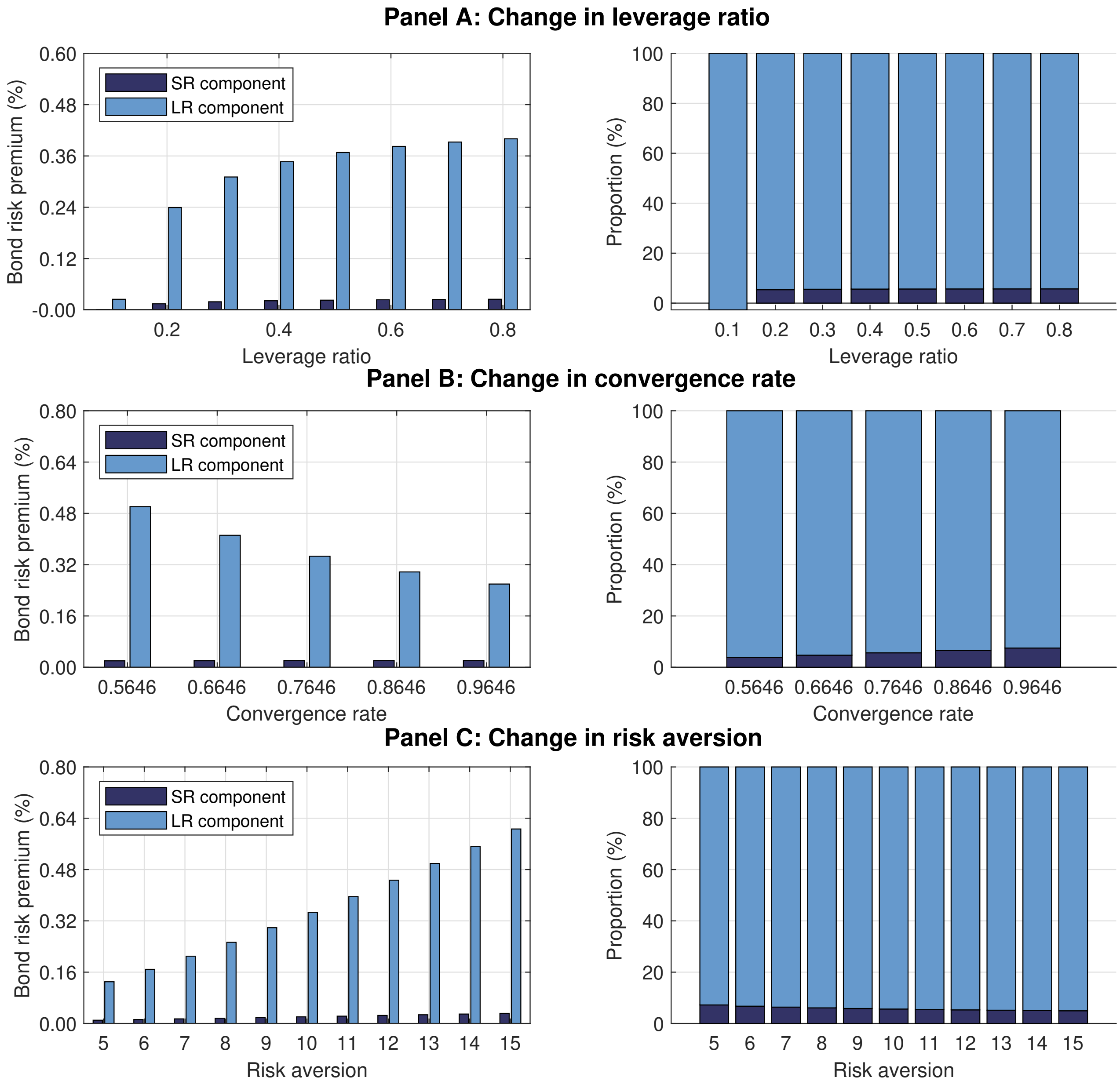

Figure A.1. **Decomposition of Bond Risk Premium**

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 IA12.

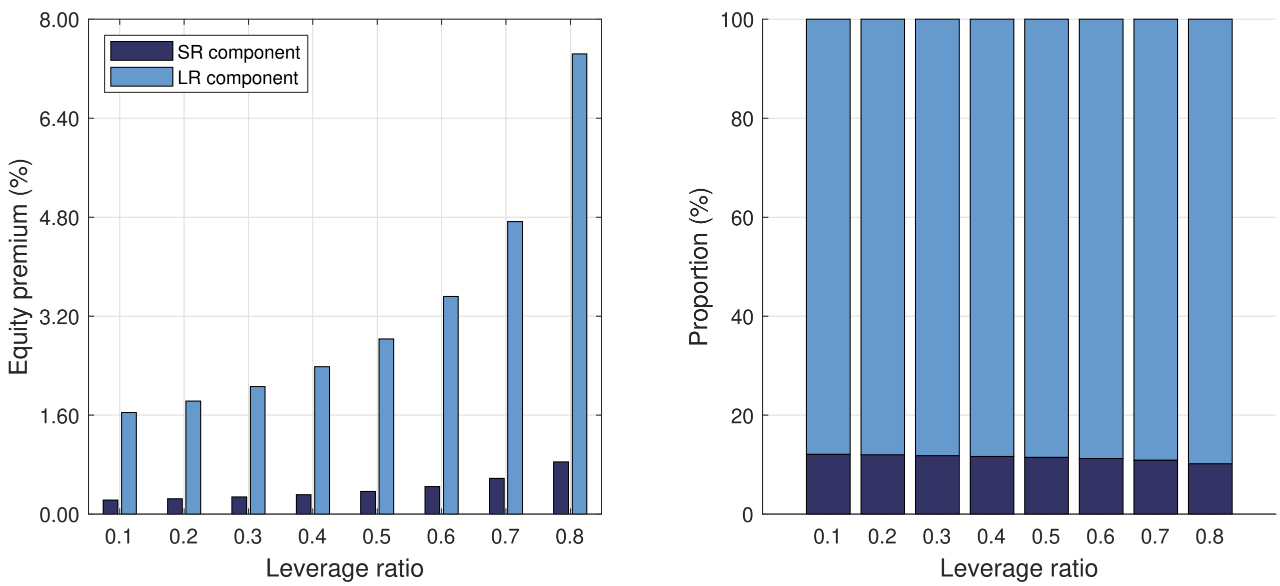

Figure A.2. **Decomposition of Equity Premium with Leverage Ratio**

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 IA12.

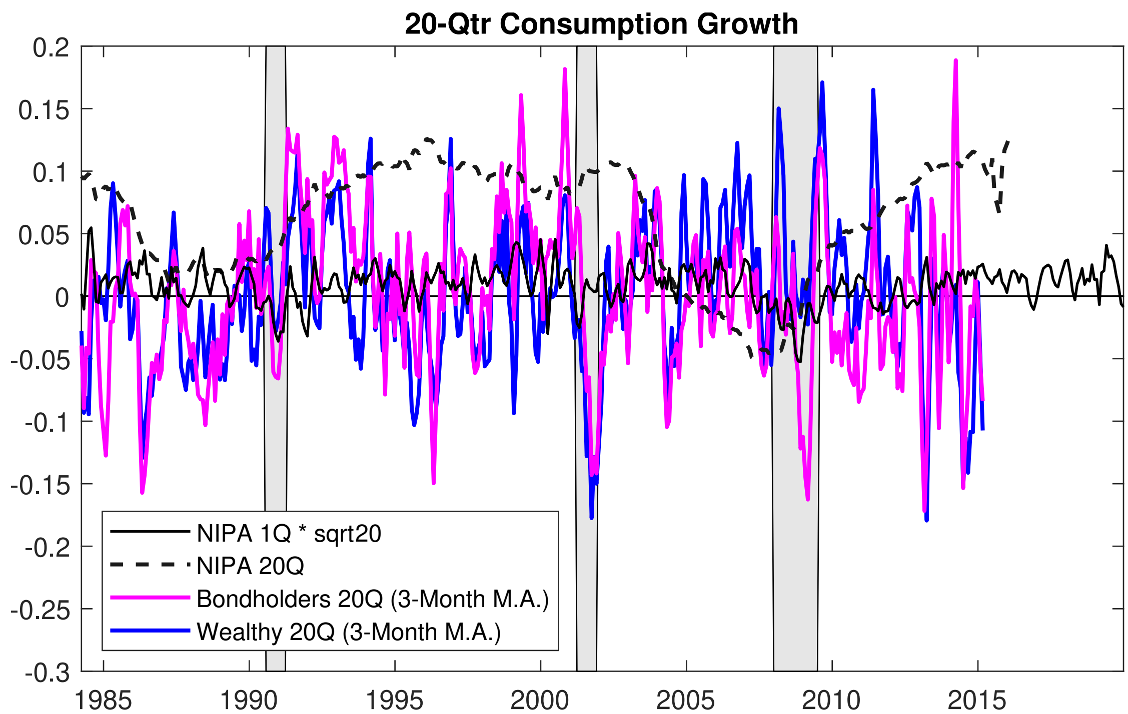

Figure A.3. **CEX 20-Qtr Consumption Growth and NIPA Consumption Growth**

This figure plots the NIPA consumption growth (1 quarter and cumulative 20 quarters) and the CEX 20-quarter consumption growth rates. The gray background shows the NBER recession.

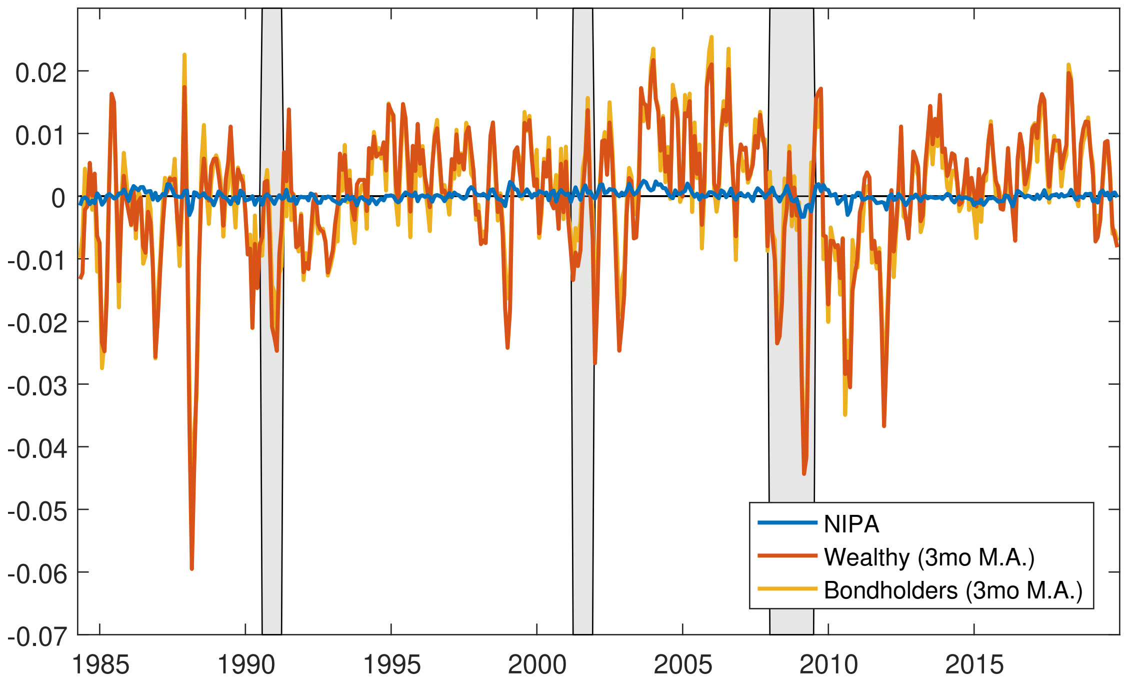

Figure A.4. **Expected Consumption Growth $E_t[\Delta c_{t+1}]$ Implied From VAR**

This figure plots $E_t[c_{t+1} - c_t]$ implied from VAR specified in Section 2.2. For each consumption series, we regress it on the same set of state variables shown in Table 6, and plot the fitted value.

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