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

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

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.

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

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

$$s_{t+1} \approx (1-\gamma)\lambda(\delta) w_{t+1} + \left(\frac{1}{\rho} - 1\right)\left(\frac{1}{2} w'_{t+1} \Theta_0 w_{t+1} + w'_{t+1} \Theta_1 x_t + \theta_1 x_t + \theta_2 w_{t+1}\right) \tag{VII.3}$$

where

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

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

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

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.

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

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: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\sigma^2(r_{i,t+1})}{2} - \frac{\sigma^2(r_{f,t})}{2} = \zeta + (\gamma - 1)c\hat{o}v(\sum_{s=0}^{S-1}\delta^s(c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) + e_i$ where $r_{i,t+1}$ is the 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	3.2×10^{-4}	0.006	0.008	1.7×10^{-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: $\hat{E}[r_{i,t+1} - r_{f,t}] + \frac{\hat{\sigma}^2(r_{i,t+1})}{2} - \frac{\hat{\sigma}^2(r_{f,t})}{2} = \zeta + (\gamma - 1)\hat{cov}(\sum_{s=0}^{S-1} \delta^s (c_{t+1+s} - c_{t+s}), r_{i,t+1} - r_{f,t}) + e_i$ 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 $\sum_{s=0}^{S-1} \delta^s (c_{t+1+s} - c_{t+s})$. 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 $(\hat{E}_{t+1} - \hat{E}_t) \sum_{s=0}^{\infty} \beta^s (c_{t+s+1} - c_{t+s}) = \epsilon_{t+1}^{SR} + \epsilon_{t+1}^{LR}$ where $c_{t+1} - c_t = \mu_c + U_c x_t + \epsilon_{t+1}^{SR}$, $x_{t+1} = G x_t + \epsilon_{t+1}^{x}$, and $\epsilon_{t+1}^{LR} = \delta U_c (I - \delta G)^{-1} \epsilon_{t+1}^{x}$, 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_{t+1}^{SR}	430	0.00	8.24	-17.93	-13.40	-5.59	-0.05	5.54	14.37	21.03
ϵ_{t+1}^{LR}	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	-3.4×10^{-4}***	5.4×10^{-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: $\hat{cov}(\sum_{s=0}^{S-1}\delta^s(c_{t+1+s}-c_{t+s}), r_{i,t+1}-r_{f,t}) = \eta + \frac{1}{(\gamma-1)}(\hat{E}[r_{i,t+1}-r_{f,t}] + \frac{\hat{\sigma}^2(r_{i,t+1})}{2} - \frac{\hat{\sigma}^2(r_{f,t})}{2}) + u_i$ 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

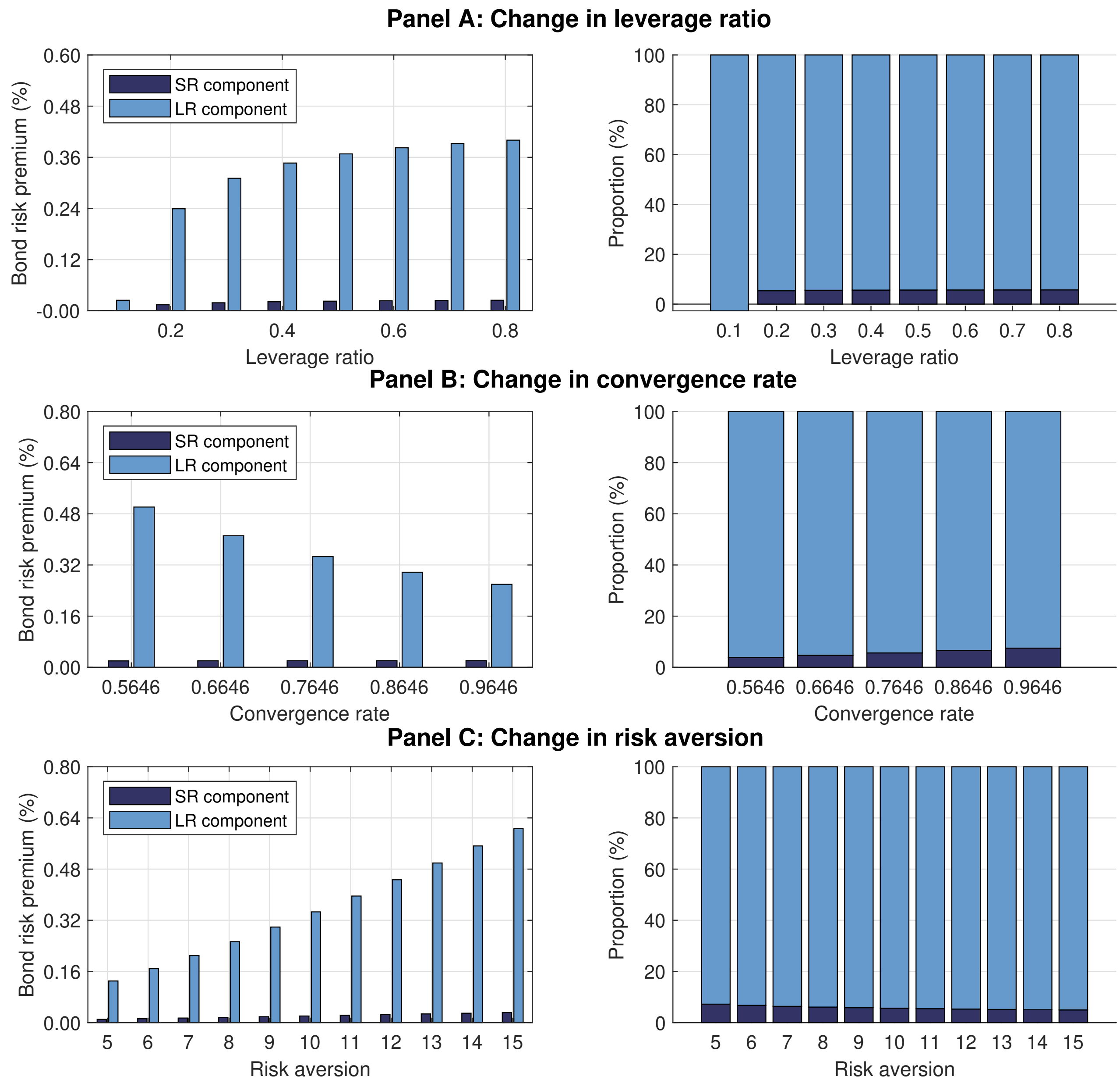

Figure A.1. **Decomposition of Bond Risk Premium**

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.

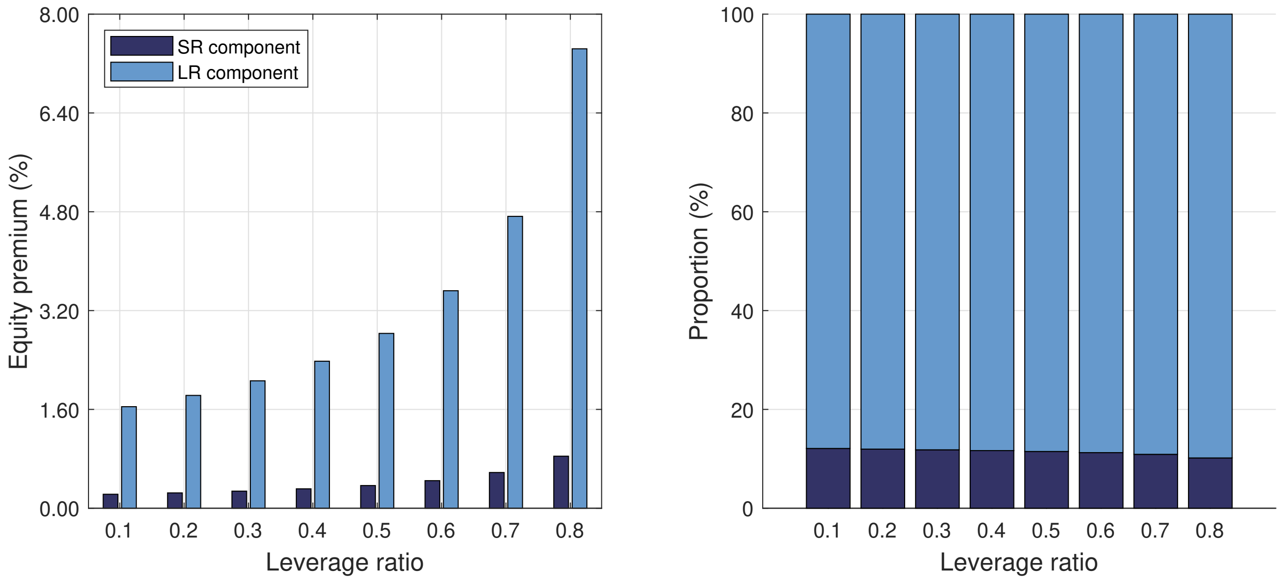

Figure A.2. **Decomposition of Equity Premium with Leverage Ratio**

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.

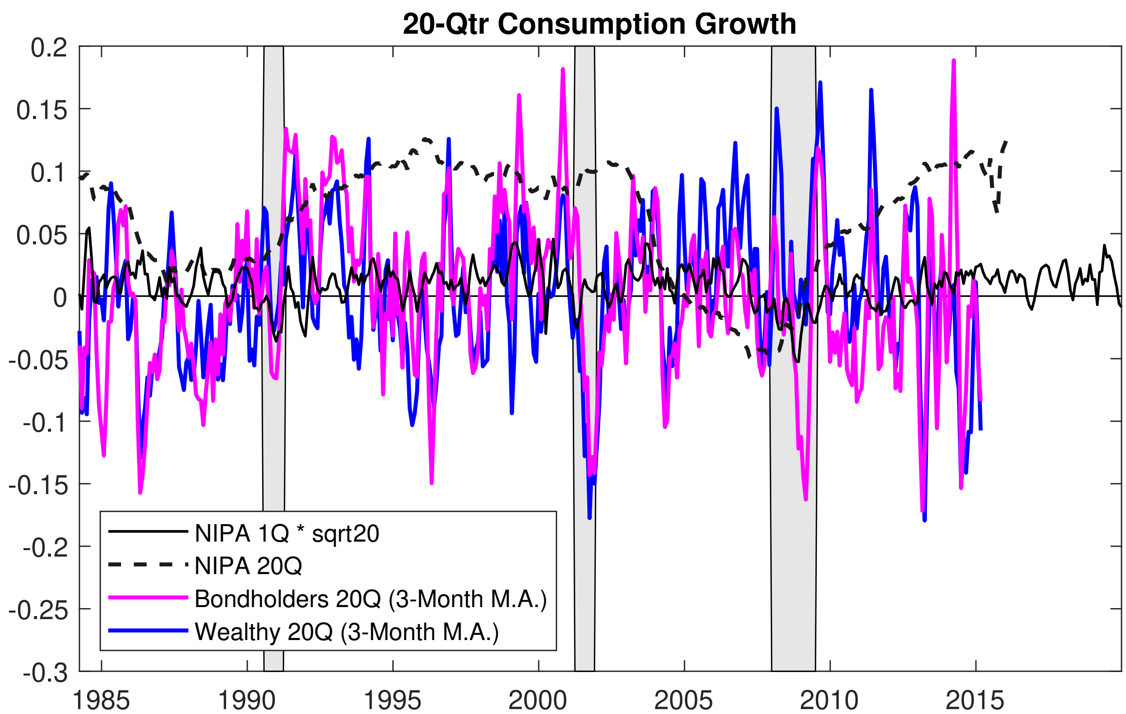

Figure A.3. **CEX 20-Qtr Consumption Growth and NIPA Consumption Growth**

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.

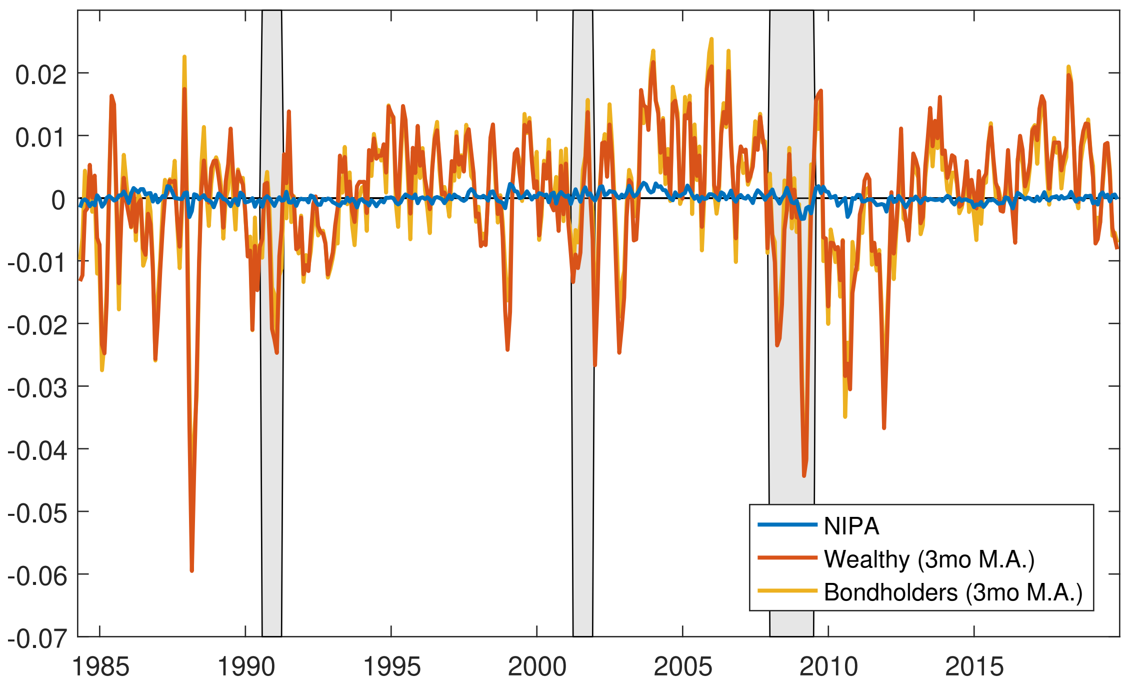

Figure A.4. **Expected Consumption Growth $E_t[\Delta c_{t+1}]$ Implied From VAR**

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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