Asset holders' Consumption Risk and Tests of Conditional CCAPM*

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Abstract

We test the conditional consumption-CAPM using asset holders' consumption and find that the time variation in the prices of asset holders' consumption risk is procyclical. This puzzling time variation is at odds with the implication of existing consumption-based equilibrium asset pricing models. We show that our finding is a salient feature of the data observed in multiple asset classes (aggregate equity market, equity portfolios, bond portfolios, and commodities portfolios), using different measures of consumption (household survey data and high-frequency retail shopping data) and alternative empirical methodologies.

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1 Introduction

The consumption-based capital asset pricing model (CCAPM)[1] is arguably one of the most elegant theories in financial economics, as it provides a fundamental understanding of the relationships between macroeconomic fundamentals and financial markets. Recent studies provide empirical support for the unconditional version of the model by measuring the consumption risk of households who own financial assets, which is theoretically more relevant for asset pricing than non-asset holders' consumption risk.[2] Despite the empirical success of asset holders' consumption risk for the unconditional version of the model, there has been no attempt to examine the ability of asset holders' consumption risk to explain asset dynamics.

In this paper, we revisit the conditional tests of CCAPM (e.g., Duffee, 2005; Nagel and Singleton, 2011; Roussanov, 2014) with asset holders' consumption for the 1985–2019 period. In doing so, we identify puzzling time variation in the price of consumption risk implied by asset holders' consumption – the price of consumption risk varies *procyclically*. This procyclical time variation in the price of consumption risk is in sharp contrast to existing major consumption-based asset pricing theories in which the price of consumption risk (risk aversion) exhibits a countercyclical variation either exogenously or endogenously.[3] The procyclical time variation in the price of consumption risk is also inconsistent with long-run

[1] See Rubinstein (1976), Breeden and Litzenberger (1978), Lucas (1978), and Breeden (1979).

[2] Empirical studies that support the unconditional model: Mankiw and Zeldes (1991), Brav et al. (2002), Paiella (2004), Balduzzi and Yao (2007), Malloy et al. (2009), and Lettau et al. (2019), among others. Theories that predict the importance of asset holders' consumption: Basak and Cuoco (1998), Gomes and Michaelides (2008), Guvenen (2009), and Elkamhi and Jo (2021), among others.

[3] Habit-formation models with exogenous countercyclical risk aversion: Constantinides (1990), Campbell and Cochrane (1999), Bekaert et al. (2009), and Bekaert and Engstrom (2017), among others. Habit-formation models with endogenous countercyclical risk aversion: Chan and Kogan (2002).

risk models or disaster risk models in which the price of consumption risk is constant.[4] We demonstrate that this puzzling time variation is a salient feature of the data observed in multiple asset classes – stocks, bonds, and commodities. In addition, the finding is robust to different consumption measures and empirical approaches.

We estimate the price of consumption risk as a linear function of conditioning variables for the aggregate equity market portfolio (CRSP value-weighted NYSE, NASDAQ, and AMEX index). To use multiple portfolios as test assets, we adopt the nonparametric estimation strategy developed by Roussanov (2014), where the price of consumption risk is estimated by exploiting the information contained in the cross-section of conditional moments of consumption growth and asset returns. For both approaches, the amount of consumption risk is flexibly estimated using locally linear estimators with an automatic selection of bandwidths without making any assumptions on the functional form of the amount of consumption risk. For the set of conditioning variables, we use the first three principal components of a large set of 162 financial and economic variables to mitigate the effects of the potential omission of investors' information in the chosen conditioning variables.[5]

To measure asset holders' consumption, we rely on the Consumer Expenditure Survey (CEX) data, which is commonly used in studies of asset holders' consumption.[6] Ideally, well-identified stockholders' (bondholders) consumption would be valid to price stocks (bonds). However, the CEX database does not distinguish stockholders from bondholders. One could impute the probability of owning stocks (bonds), using the data where the accurate own-

[4]Long-run risk models: Bansal and Yaron (2004), Bollerslev et al. (2009), Bansal et al. (2009), and Segal et al. (2015), among others. Disaster risk models: Rietz (1988), Barro (2006), Gabaix (2012), and Wachter (2013), among others.

[5]See Ludvigson and Ng (2007), Ludvigson and Ng (2009), Jurado et al. (2015), and McCracken and Ng (2016), among others.

[6]See Brav et al. (2002), Paiella (2004), Balduzzi and Yao (2007), and Malloy et al. (2009), among others.

ership of assets and demographic information are observable. However, we need to take a stand on the set of predictors of asset ownership for this approach. Thus, we simply use the consumption growth of households who own any financial assets – either stocks, mutual funds, or bonds. This approach is more transparent and valid as well to the extent that the intertemporal marginal rate of substitution (IMRS) of average asset holders mimics that of holders of each asset class. To compare asset holders' consumption risk with aggregate consumption risk, we use the National Income and Product Accounts (NIPA) to measure aggregate consumption.

We first estimate the price of consumption risk using the aggregate equity market portfolio by regressing the CRSP value-weighted market returns on nonparametrically pre-estimated conditional covariances. Then, we examine the dynamics of the estimated price of consumption risk by correlating it with the state variables.[7] We find that the price of aggregate consumption risk for the aggregate equity market varies *countercyclically*, which is consistent with previous studies on the conditional test of CCAPM and also theories of habit formation (e.g., Constantinides, 1990; Campbell and Cochrane, 1999). However, we find that the price of asset holders' consumption risk for the aggregate equity market varies *procyclically*. This finding is surprising, as it is not consistent with habit models, long-run risk models, or disaster models in which the price of risk is either countercyclical or constant.

Is the procyclical price of asset holders' consumption risk observed in multiple asset classes? We extend our analysis to multiple asset classes: 100 equity portfolios, Trea-

[7] The state variables are *sc* (stock market wealth-to-aggregate consumption ratio), detrended *sc*, *dfy* (default yield spread, i.e., the difference between BAA and AAA-rated corporate bond yields), and *yc* (labor income-to-aggregate consumption ratio). These variables are used in past studies (e.g., Duffee, 2005; Nagel and Singleton, 2011; Roussanov, 2014).

sury and spread-sorted corporate bonds, basis-sorted commodity portfolios, and forward premium-sorted currency portfolios. We find that the prices of asset holders' consumption risk for these multi-asset classes are still procyclical, while none of the portfolios using aggregate consumption produces such a procyclical pattern of the price of consumption risk. One exception is the currency portfolios. The price of asset holders' consumption risk estimated by currency portfolios is not significantly associated with the state variables, while the price of aggregate consumption risk from currency portfolios is countercyclical.

Having established the procyclical variation in the price of asset holders' consumption risk in multi-asset classes, we further examine the dynamics of the price of consumption risk within 100 equity portfolio groups. We find that the prices of asset holders' consumption risk separately estimated using 25 size/book-to-market, size/investment, and size/reversal portfolios exhibit a procyclical variation. Therefore, the procyclical dynamics of the price of asset holders' consumption risk are consistently observed for multi-asset classes as well as various equity portfolios.

To empirically understand the puzzling dynamics of the procyclical price of asset holders' consumption risk, we study the dynamics of the amount of consumption risk. We find that the amount of aggregate consumption risk exhibits a weakly procyclical variation, which is consistent with Duffee (2005), Roussanov (2014), and Xu (2021). In contrast, the amount of asset holders' consumption risk exhibits a countercyclical variation.[8] Therefore, these findings suggest that the puzzle in conditional tests of CCAPM lies in the procyclical price

[8]The countercyclical amount of consumption risk is consistent with leading representative-agent models (e.g., Campbell and Cochrane, 1999; Bekaert et al., 2009; Bekaert and Engstrom, 2017; Bollerslev et al., 2009; Bansal et al., 2009; Segal et al., 2015) and also a heterogeneous-agent model with market entry/exit (e.g., Elkamhi and Jo, 2021).

of consumption risk, not the procyclical amount of consumption risk, which is the Duffee puzzle (e.g., Duffee, 2005; Xu, 2021), as the amount of asset holders' consumption risk does not exhibit a procyclical variation.

We also revisit the conditional value premium puzzle documented by Roussanov (2014). We find that the covariances between the long-short returns of value-minus-growth and aggregate consumption growth vary countercyclically, as in Roussanov (2014). However, a different picture emerges when asset holders' consumption risk is tested. The covariances between the long-short returns of value-minus-growth and asset holders' consumption growth vary procyclically, which is in the same direction as the conditional value premium. Therefore, asset holders' consumption risk provides an explanation for the conditional value premium puzzle.

Throughout our analyses, we use the CEX data to measure asset holders' consumption and the NIPA data to measure aggregate consumption. To confirm that our findings on the procyclical price of asset holders' consumption risk are not driven by something specific to the CEX, we re-run our analyses using the aggregate consumption measure from the CEX. As opposed to the procyclical price of asset holders' consumption risk, we find that the price of aggregate consumption risk using CEX data is highly countercyclical, which is consistent with the findings of a countercyclical price of aggregate consumption risk using NIPA consumption. Therefore, our findings are not due to the data difference between the CEX and the NIPA.

Measurement errors in CEX data have been pointed out in the literature (e.g., Aguiar and Bils, 2015; Lettau et al., 2019). Thus, one could be concerned that our results are driven by measurement errors that are specific to CEX data. To address this concern, we perform an out-of-sample validation using an alternative consumption data set. We use the Consumer Panel Dataset (CPD) provided by the Kilts-Nielsen Data Center from 2004 to 2019. One challenge is that the data do not provide asset-holding information as in the CEX. We use a simple approach that exploits geographic heterogeneity in households' stock market participation captured by dividend income from IRS tax data (e.g., Lin, 2020; Durnev and Wang, 2021; Zhang, 2021). Specifically, we identify households residing in a county where dividend income to adjusted gross income is in the top 10% each year among US counties from the CPD. Using this approach, we find that our results based on the CPD data are consistent with CEX data – the price of asset holders' (aggregate) consumption risk varies procyclically (countercyclically) for multiple asset classes.

Our paper contributes to the literature on tests of the conditional version of the consumption CAPM (e.g., Duffee, 2005; Nagel and Singleton, 2011; Roussanov, 2014) by providing novel empirical evidence that the price of asset holders' consumption risk is procyclical. Moreover, we provide an explanation for the two puzzles raised in the literature: (1) The Duffee puzzle – the amount of aggregate consumption risk varies procyclically for the aggregate equity market portfolio, while equity premium varies countercyclically (Duffee, 2005). (2) The conditional value premium puzzle – the amount of aggregate consumption risk for the value-minus-growth portfolios varies countercyclically, while the conditional value premium varies procyclically (Roussanov, 2014). We show that when asset holders' consumption is used, which is more consistent with theories than aggregate consumption, the time variation in the amount of consumption risk well aligns with return dynamics for both the aggregate equity market portfolio and value-minus-growth portfolios.

Our paper also contributes to the literature that focuses on a subset of aggregate consumption that is more linked to the stochastic discount factor (e.g., Malloy et al., 2009; Lettau et al., 2019; Elkamhi et al., 2022). While past studies examine the unconditional implications of asset holders' consumption risk, we study the conditional implications of asset holders' consumption risk.[9] We provide evidence that shows a superior pricing performance of the CCAPM using asset holders' consumption relative to aggregate consumption, consistent with existing studies.

Last but not least, our paper is related to studies that question the empirical plausibility of habit formation models (e.g., Dynan, 2000; Brunnermeier and Nagel, 2008; Sahm, 2012). Most of these studies find evidence that favors constant relative risk aversion. However, different from them, our findings are not consistent with countercyclical relative risk aversion or constant relative risk aversion.

The rest of this paper is organized as follows. Section 2 discusses the conditional CCAPM. Section 3 describes our econometric approach and data. Section 4 presents the empirical results. Section 5 concludes the paper.

2 The conditional CCAPM

In this section, we describe the theoretical background of our test. A representative agent consumption-based asset pricing model implies that the conditional excess returns of a risky asset i at time t is the price of consumption risk at time t multiplied by the amount

[9] In addition to the fact that our study performs conditional tests, our paper is also different from Lettau et al. (2019) in that we directly use asset holders' consumption while they use an indirect measure of asset holders' consumption, which is the capital share.

of consumption risk at time t:[10]

$$E_t[R^e_{i,t+1}] = \underbrace{\gamma_t}_{\textit{Price of risk}} \cdot \underbrace{Cov_t(R^e_{i,t+1}, \Delta C_{t+1}/C_t)}_{\textit{Amount of risk}}, \tag{1}$$

where $E_t[\,\cdot\,]$ is the conditional expectation operator, $R^e_{i,t+1}$ is the return on any risky asset i in excess of the risk-free rate, γ_t is the relative risk aversion coefficient of the representative agent, $Cov_t[\,\cdot\,]$ is the conditional covariance, and $\Delta C_{t+1}/C_t$ is the consumption growth of the representative agent. If the representative agent has constant relative risk aversion (CRRA) preferences, the price of risk is time-invariant $\gamma_t = \gamma$. In habit-formation models (e.g., Constantinides, 1990; Campbell and Cochrane, 1999; Bekaert et al., 2009; Bekaert and Engstrom, 2017), the price of risk is assumed to follow a specific countercyclical time-varying process γ_t. Long-run risk models (e.g., Bansal and Yaron, 2004; Bollerslev et al., 2009; Bansal et al., 2009; Segal et al., 2015) and disaster risk models (e.g., Rietz, 1988; Barro, 2006; Gabaix, 2012; Wachter, 2013) have a constant price of consumption risk and additional sources of risk that enter the equilibrium risk premium equation.

Models with heterogeneous risk-averse agents predict the following equilibrium equation for risk premium (e.g., Chan and Kogan, 2002; Cvitanić et al., 2012; Gârleanu and Panageas, 2015; Cochrane, 2017; Elkamhi and Jo, 2021):

$$E_t[R^e_{i,t+1}] = \underbrace{\frac{\sum_{j\in h_t} C_{j,t}}{\sum_{j\in h_t} \frac{C_{j,t}}{\gamma_j}}}_{\textit{Price of risk}} \cdot \underbrace{Cov_t(R^e_{i,t+1}, \frac{\Delta \sum_{j\in h_t} C_{j,t+1}}{\sum_{j\in h_t} C_{j,t}})}_{\textit{Amount of risk}}, \tag{2}$$

[10] This equation holds regardless of preferences. Please see the Online Appendix OA.1 for the proof. The long-run risk model of Bansal and Yaron (2004) and disaster models of Gabaix (2012) and Wachter (2013), which are based on recursive preferences, have extra terms in addition to $\gamma_t Cov_t(R^e_{i,t+1}, \Delta C_{t+1}/C_t)$. However, we focus on the term related to consumption risk only, following the studies of the conditional CCAPM.

where h_t is the index for asset ***h***olders. In a setup with heterogeneous risk-averse agents, the price of consumption risk is the asset holders' consumption-weighted harmonic mean of risk aversions, and the amount of consumption risk is the conditional covariance between asset excess returns and asset holders' consumption growth. Chan and Kogan (2002) show that without any changes in the composition of stockholders' consumption, the consumption re-distribution effect leads to a countercyclical variation in the price of risk. In bad states, the consumption of the relatively risk-tolerant agents declines the most in response to a negative shock because they heavily invest in the stock market. This change increases the consumption weights of relatively risk-averse investors, raising the consumption-weighted mean of stockholders' risk aversion. Therefore, existing theories predict either constant or countercyclical price of consumption risk exogenously or endogenously.

Prior tests of the conditional CCAPM only use aggregate consumption based on the assumption of a representative-agent economy where asset holders' consumption is the same as aggregate consumption. However, the aforementioned heterogeneous-agent models predict that in a world where there are both asset holders and non-asset holders, it is the consumption of asset holders that is directly linked to the stochastic discount factor. Moreover, empirical studies emphasize the importance of asset holders' consumption versus non-asset holders' consumption in explaining the cross-section of asset returns.[11] Therefore, different from prior conditional tests that use aggregate consumption, we test the ability of asset holders' consumption risk to explain the conditional version of the consumption CCAPM. In doing so, we also test the representative agent model using aggregate consumption for

[11] Mankiw and Zeldes (1991), Brav et al. (2002), Paiella (2004), Balduzzi and Yao (2007), Malloy et al. (2009), Lettau et al. (2019), and Elkamhi et al. (2022), among others.

the following two reasons. First, the analysis of the conditional CCAPM using aggregate consumption provides a benchmark against which we can compare the model using asset holders' consumption. This allows us to rule out the possibility that our findings on asset holders' consumption are driven by our choices of methodologies or conditioning variables. Second, by conducting tests based on aggregate consumption, we can confirm whether our results are consistent with the findings in the literature, which helps to assess the validity of our econometric implementation.

3 Econometric approach and data

In this section, we first discuss the econometric methodologies in Subsection 3.1. Then, we describe the data in Subsection 3.2.

3.1 Econometric approach

3.1.1 Estimation of conditional covariances

For the first step to estimate the conditional covariances (amount of risk), we run the following one-step-ahead (3-month) predictive regressions for an asset $i, \ \forall i = 1, ..., N$:

$$R^e_{i,t+1} = a_r' Y_{r,t} + e_{r_i,t+1}, \qquad \Delta C_{t+1}/C_t = a_c' Y_{c,t} + e_{c,t+1}, \tag{3}$$

where $Y_{r,t}$ is a set of instrument variables for asset returns; $Y_{c,t}$ is a set of instrument variables for consumption growth; $R^e_{i,t+1}$ denotes 3-month asset returns in excess of the 3-month risk-free rate; $\Delta C_{t+1}/C_t$ is 3-month consumption growth; C_t is either NIPA aggregate consumption, CEX asset holders' consumption, CEX aggregate consumption, NielsenIQ asset holders' consumption, or NielsenIQ aggregate consumption. In our setting, a change from t to $t+1$ denotes a 3-month change, as CEX data provide 3-month consumption growth at a monthly frequency. To capture investors' information sets, we use the first three principal components of 162 economic and financial variables as a set of conditioning variables $z_t = [F_{1,t}\ F_{2,t}\ F_{3,t}]'$, which is a $K \times 1$ matrix ($K = 3$) that enters $Y_{r,t}$ and $Y_{c,t}$ as follows: $Y_{r,t} = [1\ z_t]'$ and $Y_{c,t} = [1\ z_t\ \Delta C_t/C_{t-1}\ \Delta C_{t-1}/C_{t-2}\ \Delta C_{t-2}/C_{t-3}]'$. We include lagged variables of consumption growth at t, $t-1$, and $t-2$ as in Duffee (2005).[12] Then, ex-post realized covariances are the product of the fitted residuals of asset returns and consumption growth:

$$Cov^*(R^e_{i,t+1}, \Delta C_{t+1}/C_t) \equiv \hat{e}_{r_i,t+1}\hat{e}_{c,t+1} \tag{4}$$

Finally, we estimate the conditional covariances ($\widehat{Cov}_t(R^e_{i,t+1}, \Delta C_{t+1}/C_t)$) by projecting ex-post covariances on the set of conditioning variables z_t:

$$Cov^*(R^e_{i,t+1}, \Delta C_{t+1}/C_t) = \widehat{Cov}_t(R^e_{i,t+1}, \Delta C_{t+1}/C_t) + u_{t+1} \tag{5}$$

In estimating conditional covariances, we do not impose a restrictive parametric assumption on the functional form of the conditional covariances. Instead, we adopt a nonparametric estimation (e.g., Harvey, 2001; Nagel and Singleton, 2011; Roussanov, 2014; Rossi and Timmermann, 2015). Thus, the conditional covariances are estimated flexibly in a nonparametric way as a function of conditioning variables, using the Epanechnikov kernel function, $\mathbb{K}(\cdot)$:

$$W_t = \frac{\mathbb{K}(\frac{dist_t}{h})}{\mathbf{1}_T'\mathbb{K}(\frac{dist_t}{h})}, \quad \mathbb{K}(u) = (1-u^2)\mathbb{1}(|u|<1), \tag{6}$$

where $dist_t = \sqrt{\sum_{k=1}^{K}(\mathbf{1}_T z_{k,t} - z_k)^2}$ ($T \times 1$ vector); K is the number of conditioning variable; W_t is a $T \times 1$ local-weighting matrix; $\mathbb{1}(|u| < 1)$ is an indicator that takes a value of one

[12] In Subsection 4.5.4, we show that our results are robust to an alternative specification where the set of conditioning variables z_t is removed for $Y_{r,t}$ and $Y_{c,t}$.

if $|u| < 1$; h is a bandwidth. h is automatically selected using the bias-corrected Akaike Information Criterion (Hurvich et al., 1998):

$$AICC = log(\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2) + 1 + \frac{2(tr(L)+1)}{T - tr(L) - 2}, \tag{7}$$

where y_t is an ex-post covariance; $\hat{y}_t$ is the conditional covariance; L is a smoothing matrix such that $\hat{\boldsymbol{Y}} = L\boldsymbol{Y}$, $\boldsymbol{Y} = [y_1\ y_2\ ...\ y_T]'$, and $\hat{\boldsymbol{Y}} = [\hat{y}_1\ \hat{y}_2\ ...\ \hat{y}_T]'$. For robustness, we also adopt the generalized cross-validation (Craven and Wahba, 1978):

$$GCV = (\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2)/(1 - T^{-1}tr(L))^2 \tag{8}$$

3.1.2 Estimation of the price of risk at the market level

For the aggregate equity market (CRSP value-weighted NYSE, NASDAQ, and AMEX index) as a single test asset ($N = 1$), we estimate the price of consumption risk by regressing the aggregate equity market returns on nonparametrically pre-estimated conditional covariances:

$$R^e_{m,t+1} = \alpha + (\gamma_0 + \gamma_1' z_t)\widehat{Cov}_t(R^e_{m,t+1}, \Delta C_{t+1}/C_t) + \epsilon_{t+1}, \tag{9}$$

where $R^e_{m,t+1}$ is the 3-month returns of the CRSP value-weighted index at time $t+1$ in excess of the 3-month returns of 30-day T-bill as of time t, and $\widehat{Cov}_t(R^e_{m,t+1}, \Delta C_{t+1}/C_t)$ is the nonparametrically pre-estimated conditional covariance between equity returns and consumption growth. In this case, as in Duffee (2005), the price of risk ($\hat{\gamma}_t$) is a linear function of the set of conditioning variables z_t ($K \times 1$ matrix):

$$\hat{\gamma}_t = \hat{\gamma}_0 + \hat{\gamma}_1' z_t \tag{10}$$

3.1.3 Estimation of the price of risk at the portfolio level

For our portfolio tests ($N > 1$), we rely on the approach developed by Roussanov (2014) which does not impose a functional form for the price of risk. We do so because imposing linearity on the specification of the price of risk could lead to a spurious assessment of the model, as pointed out in Brandt and Chapman (2018). In this approach, the price of risk is estimated nonparametrically by exploiting the information contained in the cross-section of conditional moments of consumption growth and asset returns. This approach is robust to the misspecification of both the conditional moments and the prices of risk. Specifically, based on the pre-estimated conditional covariance for each asset, the conditional price of risk is estimated at each point in time using the cross-sectional regression. The price of risk in this specification is designed to vary as a non-linear function of the set of conditioning variables z_t, reflecting the time-varying cross-sectional relation between return and risk. In this approach, the price of consumption risk is given by:

$$[\hat{\alpha}_t \;\; \hat{\gamma}(z_t)]' = \arg\min_{\alpha,\, \gamma} \boldsymbol{g}(z_t)' W \boldsymbol{g}(z_t), \tag{11}$$

where $\boldsymbol{g}(z_t) = \hat{E}_t[\mathbf{R}^e_{t+1}] - \alpha_t - \gamma(z_t)\widehat{Cov}_t(\mathbf{R}^e_{t+1}, \Delta C_{t+1}/C_t)$, and W is an $N \times N$ weighting matrix. Let the $N \times 1$ vector of the conditional expectation of excess returns estimated by z_t be denoted by $\hat{\mathbf{m}}(z_t)$ and the $N \times 2$ vector of ones and estimated conditional covariances be denoted by $\hat{\mathbf{cv}}(z_t)$. Then, the non-linear price of risk is given by the weighted least squares:

$$[\hat{\alpha}_t \;\; \hat{\gamma}(z_t)]' = (\hat{\mathbf{cv}}(z_t)' W \hat{\mathbf{cv}}(z_t))^{-1} \hat{\mathbf{cv}}(z_t)' W \hat{\mathbf{m}}(z_t) \tag{12}$$

For the weighting matrix W, we use the identity matrix as in Roussanov (2014).

3.1.4 Evaluation of dynamics of the price and amount of risk

To assess the dynamics of the estimated price and amount of risk, we run simple time-series regressions of the price of risk or amount of risk separately on each of the four state variables:

$$\hat{\gamma}_t = a + \beta X_t + \epsilon_t, \tag{13}$$

$$\widehat{Cov}_t(R^e_{t+1}, \Delta C_{t+1}/C_t) = a + \beta X_t + \epsilon_t, \tag{14}$$

where X_t is either *sc* (stock market wealth-to-aggregate consumption ratio), detrended *sc*, *dfy* (default yield spread, i.e., the difference between BAA and AAA-rated corporate bond yields), or *yc* (labor income-to-aggregate consumption ratio). We rely on multiple conditioning variables in order to comprehensively assess the dynamics of the estimated price and amount of risk given the unobservable nature of economic states. Online Appendix Figure OA.1 plots the time-series of the four state variables. Detrended *sc* and *sc* vary procyclically, because, in good states, stock market wealth increases more rapidly than consumption. *dfy* and *yc* vary countercyclically because in good states, default risks go down and labor income becomes less important than financial income for consumption (composition effect).[13]

It is worth noting that while the price and amount of risk are estimated nonparametrically, we assess their dynamics in a linear way. It is possible that the price and amount of risk are associated with the state variables in a nonlinear way. However, the assessment

[13] Other studies use one of these state variables, considered in our study, as a single conditioning variable (e.g., Duffee, 2005; Nagel and Singleton, 2011; Roussanov, 2014). Then, the direction of dynamics of the conditional covariances is determined based on the sign of the relationship between ex-post covariances and a state variable. Unlike these past studies which use a single conditioning variable, we use multiple principal components of a large set of variables as a set of conditioning variables. Therefore, we cannot correlate the state variables with ex-post covariances to determine the dynamics of the amount of risk. Instead, we regress the estimated price or amount of risk on one of the state variables.

of the dynamics in a nonlinear way increases a researcher's degree of freedom relative to the above-mentioned simple linear regression since, for the nonlinear assessment, there are various ways to present the statistical significance of the relationship between the price or amount of risk and the state variables. Thus, for transparency and simplicity, we adopt a simple linear regression and consider multiple state variables.

3.2 Data

In this subsection, we describe the data sources and variables used in our study. The data frequency is monthly. All of the test assets and consumption data sets are from February 1985 to December 2019 period. The starting month is determined by the availability of corporate bond data. The ending month is determined by the availability of NielsenIQ consumer panel data.

3.2.1 Test Assets

Equity. For the aggregate equity market, we use the stock market index defined as the CRSP value-weighted NYSE/NASDAQ/AMEX index that includes distributions. For equity portfolios, we use 100 equity portfolios, consisting of 25 size/book-to-market sorted portfolios (Size/BM), 25 size/investment sorted portfolios (Size/INV), 25 size/operating profitability portfolios (Size/OP), and 25 size/long-term reversal portfolios (size/REV). The CRSP value-weighted index is from the Center for Research in Security Prices (CRSP), and all of the equity portfolios are from Kenneth French's website.

Bonds. For bonds, we use government and corporate bond portfolios as in He et al. (2017). For government bonds, rates of 90-day and, 1-, 2-, 5-, 7-, 10-, 20-, and 30-year government bonds are used. For corporate bonds, we use ten portfolios sorted on credit spreads from

Nozawa (2017). These portfolios are constructed based on a comprehensive panel data set collected from Lehman Brothers, TRACE, NAICS, and DataStream databases. As there are no observations for January 1985, our sample period begins in February 1985. Based on clean prices and accrued interest, the monthly return on a corporate bond in month t is calculated as

$$R_t = \frac{P_t + AI_t + Coupon_t}{P_{t-1} + AI_{t-1}} - 1, \tag{15}$$

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

Commodities. For commodities, we use five basis-sorted commodity portfolios (Yang, 2013). The portfolios are constructed using the data from the S&P GSCI commodity excess return indices from the Bloomberg terminal, which include the 24 commodities listed in Table D4 of Koijen et al. (2018) as well as platinum, palladium, and orange juice.[14] These indices measure the return from investing in near-term S&P GSCI futures and rolling them forward each month (on the fifth to ninth business days of each month), always keeping investment in near-term futures.

Currencies. For currencies, we use six portfolios sorted on forward premiums (Lettau et al., 2014), which are based on 48 currencies. The returns of the currency of a country k are defined as

$$R_{k,t+1} = \frac{S_t}{S_{t+1}}(1 + i_{k,t}) - 1 = \frac{F_t}{S_{t+1}}(1 + i_{US,t}) - 1, \tag{16}$$

where S_t and F_t are the spots and future exchange rate, respectively, expressed in foreign currency per US dollar, and $i_{k,t}$ and $i_{US,t}$ are the foreign and US interest rate, respectively.

[14] 24 list is crude oil, gas oil, WTI crude, gasoline, heating oil, natural gas, cotton, coffee, cocoa, sugar, soybeans, Kansas wheat, corn, wheat, lean hogs, feeder cattle, live cattle, gold, silver, aluminum, nickel, lead, zinc, and copper.

The spot and the 1-month forward exchange rates are from the WMR (WM/Reuters).

3.2.2 Consumption measures

NIPA Aggregate consumption. NIPA aggregate consumption is the seasonally adjusted real per capita expenditures on nondurables and services from the National Income and Product Accounts (NIPA) of the Bureau of Economic Analysis. As Consumer Expenditure Survey (CEX) database provides 3-month consumption growth, we also compute the 3-month consumption growth rates at a monthly frequency for NIPA aggregate consumption. The real per capita consumption is computed, using 2012 US dollars and the US population.

CEX consumption. To measure asset holders' consumption, we use the Consumer Expenditure Survey data collected by the Bureau of Labor Statistics (BLS). The CEX is a natural choice to measure asset holders' consumption, as the data contains information about the consumption together and the financial wealth of US households. As each selected household is interviewed five times at 3-month intervals, we can compute the 3-month consumption growth for each household. The BLS conducts the survey every month, and each month introduces some new households and drops the households that have completed the fifth and last interview. Therefore, a different set of households is interviewed every month, and we can compute the 3-month stockholders' consumption growth at a monthly frequency. Using 2012 dollars and family size, we compute the seasonally adjusted real per capita consumption at the household level and the mean of consumption growth across asset holders.

With respect to the identification of asset holders, asset holders are defined as households who own any financial assets – stocks, bonds, mutual funds, or other such securities, as in Vissing-Jørgensen (2002) and Malloy et al. (2009). Ideally, for our multi-asset classes setting, using well-identified stockholders' (bondholders) consumption would be valid to price stocks (bonds). However, the CEX database does not separate stockholders from bondholders or those who hold commodities or currencies. To the best of our knowledge, there is no data that provides such information together with consumption information. One way to address this issue is to impute the probability of owning stocks or bonds using data such as the Survey of Consumer Finances in which accurate asset ownership and demographic information are observed. This approach, however, unavoidably involves estimation errors as well as the researcher's arbitrary choice of specification for imputation. Therefore, we adopt the aforementioned simple approach, which is transparent and valid to the extent that the IMRS of average asset holders mimics that of holders of each asset class.

NielsenIQ Consumer Panel Dataset. To demonstrate that our results are not specific to the CEX data, we also rely on another consumption data source, which is the NielsenIQ Consumer Panel Dataset (CPD) provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business, available for the period from 2004 to 2019. The CPD data set contains longitudinal panel data that track the detailed purchases and demographic information of approximately 38,000-70,000 geographically dispersed and demographically balanced US households at a daily frequency.[15] The data provide when, where, and what the panelists purchase, and at what price with a 12-digit Universal Product Code (UPC), which is the most granular level of product identification. Products include all NielsenIQ-

[15] Demographic variables include household size, income, age, presence and age of children, employment, education, marital status, occupation, type of residence, and race. These variables are recorded for the entire household and the head of household, as well as demographics for other household members. For the sample period from 2004 to 2019, used in our tests, the annual average number of households is 62,040. The lowest number of households is 38,863 in 2005, and the highest number of households is 69,247 in 2010.

tracked categories of items from retail outlets and online shopping. NielsenIQ estimates that about 30% of household consumption is accounted for by their consumer panel data categories. NielsenIQ samples all states (except Alaska and Hawaii) and 52 Nielsen-Defined Scantrack areas plotted in Online Appendix Figure OA.2. For both CEX and NielsenIQ CPD data, we regress consumption growth on family size growth and monthly dummies at the household level to account for changes in consumption due to changes in family size and seasonality.

We exploit zip code information for each household in the NielsenIQ CPD database and merge the data with the data from the Internal Revenue Service (IRS) Statistics of Income to capture the consumption of households who are likely to hold financial assets based on the location of the households. The IRS data are an effective way to measure local stock market participation because they are based on all households that file federal tax returns in the US. For this reason, the IRS data are widely used to measure local stock market participation (e.g., Brown et al., 2008; Saez and Zucman, 2016; Lin, 2020; Chodorow-Reich et al., 2021; Crane et al., 2021; Hu et al., 2021; Gelman and Shoham, 2022). Furthermore, Brown et al. (2008) demonstrate that dividend income is a good proxy for stock ownership by comparing the IRS data with the Survey of Consumer Finances data. Following the literature, we use the ratio of aggregate dividend income over adjusted gross income as a measure of stock market participation at the county level. Then, for each year, we aggregate the consumption growth of all of the households in each county whose dividend income to adjusted gross income ratio is in the top 10 percentile in the US at the end of the previous year. We use the consumption of these households as a proxy for asset holders' consumption in the NielsenIQ CPD data. Online Appendix Figure OA.3 plots the dividend–income ratios across US counties in 2019.

To evaluate whether this identification strategy is valid, we compare the demographic characteristics of households in the top 10% counties with the rest of the sample households in the NielsenIQ CPD data. Online Appendix Table OA.1 shows that households who live in one of the top 10% counties in terms of dividends/income are more educated (fewer high school degrees and more college degrees), older, and likely to earn more income than the rest of the sample households in the NielsenIQ CPD data. The same demographic patterns are observed for asset holders versus non-asset holders in the CEX data and the SCF (Survey of Consumer Finances), which provide asset-holding information. Therefore, the differences in demographic features between likely asset holders and non-asset holders in the NielsenIQ CPD support the validity of our identification strategy for the NielsenIQ CPD.

3.2.3 Conditioning variables

A major challenge of the conditional test of asset pricing models is that econometricians do not observe a set of information available to investors at each point in time and therefore test results depend on the choice of conditioning variables as pointed out by Harvey (2001) and Duffee (2005). If the information that investors use is omitted in the chosen conditioning variables, measures of conditional moments can lead to a spurious assessment of the model (Hansen and Richard, 1987). Nevertheless, in practice, econometricians are constrained to choose only a few conditioning variables because expanding the conditioning variable set is subject to the “curse of dimensionality" (Brandt, 1999; Ludvigson and Ng, 2007).

To address this issue, we use the first three principal components of a large set of 162 financial and economic variables (e.g., Ludvigson and Ng, 2007, 2009; Jurado et al., 2015; McCracken and Ng, 2016). In this approach, the large set of conditioning variables is summarized in the three factors (z_t). The list of 162 variables is described in Online Appendix Table OA.2.

Table 1 reports the summary statistics of the 3-month returns of the test assets and the 3-month growth of consumption measures. Panel A shows that the returns and the volatility of asset returns are consistent with He et al. (2017). For example, among non-equity asset classes, commodities exhibit the highest volatility, followed by currencies, and bonds. Also, equities exhibit the highest average returns. Panel B shows that the means of the CEX and NielsenIQ consumption measures are closer to zero than the NIPA aggregate consumption data, as they are de-meaned with monthly dummies to account for seasonality. The US total aggregate consumption growth based on the NIPA is much smoother than that based on the aggregate consumption data from the CEX. Kroencke (2017) points out that the filtering of the NIPA consumption data, which is meant to mitigate measurement error, leads to such smooth consumption growth. Moreover, CEX asset holders' consumption is more volatile than CEX aggregate consumption. Similarly, NielsenIQ asset holders' consumption is more volatile than the NielsenIQ aggregate consumption, which is consistent with previous findings that asset holders' consumption is more volatile than non-asset holders (e.g., Mankiw and Zeldes, 1991; Malloy et al., 2009; Elkamhi et al., 2022).

[Insert Table 1 here]

Figure 1 displays a time series of the 3-month growth rates of consumption used in our study from April 1985 to December 2019. Asset holders' consumption is more volatile than aggregate consumption both for the CEX and the NielsenIQ, although the difference between asset holders' consumption and non-asset holders' consumption is less notable for the NielsenIQ than the CEX. In addition, it appears that both CEX and NielsenIQ data are not strongly correlated with NIPA data.

[Insert Figure 1 here]

4 Empirical results

In this section, we present the results of our empirical tests.

4.1 Dynamics of the price of consumption risk

4.1.1 Multi-asset classes

Aggregate equity market portfolio. We first estimate the conditional price of risk using the CRSP aggregate equity market portfolio by regressing the aggregate equity market returns on the conditional covariances, assuming that the price of risk is a linear function of the first three principal components of the 162 variables. Figure 2 plots the estimated price of risk implied by either NIPA aggregate consumption or CEX asset holders' consumption. We plot the estimated prices of risk together with the detrended *sc* and NBER recessions. The price of risk implied by NIPA aggregate consumption increases notably during recessions and varies in the opposite direction of the detrended *sc*, suggesting a countercyclical variation in the price of aggregate consumption risk. This time variation in the price of risk is largely consistent with other studies using NIPA aggregate consumption data (e.g., Duffee, 2005; Nagel and Singleton, 2011; Roussanov, 2014) and habit-formation models (e.g., Campbell and Cochrane, 1999). The price of risk implied by asset holders' consumption, however, notably exhibits a procyclical variation: it varies in the opposite direction of the price of risk implied by aggregate consumption. Also, it decreases during every recession.

[Insert Figure 2 here]

More formally, we run a simple regression of the estimated prices of risk using the CRSP aggregate equity market portfolio on the state variables. All of the state variables are standardized to a unit standard deviation for ease of interpretation. The first row of Panel A of Table 2 shows that the price of risk implied by NIPA aggregate consumption is negatively associated with the procyclical state variables (t-stat $= -7.40$ for detrended *sc* and t-stat $= -5.75$ for *sc*) and positively associated with the countercyclical state variables (t-stat $=$ 2.40 for *dfy* and t-stat $= 4.98$ for *yc*), suggesting a countercyclical variation in the price of aggregate consumption risk.

In contrast, the first row of Panel B shows the opposite sign for each state variable when asset holders' consumption is used to estimate the price of risk using the CRSP aggregate equity market portfolio. The price of risk implied by asset holders' consumption is positively associated with detrended *sc* (t-stat $= 2.94$) and *sc* (t-stat $= 3.72$) and negatively associated with *dfy* (t-stat $= -13.44$) and *yc* (t-stat $= -2.18$). This suggests that the price of consumption risk implied by asset holders' consumption exhibits a strong procyclical variation. This is surprising, as major theories of equilibrium asset pricing do not predict such a time variation in the price of consumption risk either exogenously or endogenously. For example, habit formation models assume a countercyclical price of consumption risk (e.g., Constantinides, 1990; Campbell and Cochrane, 1999; Bekaert et al., 2009; Bekaert and Engstrom, 2017). Heterogeneous models with fixed market participation predict a countercyclical price of consumption risk endogenously through the consumption re-distribution effect (e.g., Chan and Kogan, 2002). The price of consumption risk is constant in long-run risk models (e.g., Bansal and Yaron, 2004; Bollerslev et al., 2009; Bansal et al., 2009; Segal et al., 2015) and disaster risk models (e.g., Rietz, 1988; Barro, 2006; Gabaix, 2012; Wachter, 2013). Therefore, the empirically observed procyclical time variation in the price of asset holders' consumption risk cannot be explained by existing consumption-based equilibrium asset pricing models.

[Insert Table 2 here]

Multiple equity portfolios. Is the procyclical price of asset holders' consumption risk observed in multiple equity portfolios? The second and third rows of Panel A of Table 2 show the countercyclical price of aggregate consumption risk estimated using the information contained in the cross-section of conditional equity risk premia and conditional amount of consumption risk, using the estimation strategy by Roussanov (2014). For both prices of risk estimated using Fama–French 25 size/book-to-market sorted portfolios (FF25) and 100 equity portfolios, they are significantly negatively associated with the procyclical state variables. In contrast, the second and third rows of Panel B show that the prices of asset holders' consumption risk are positively associated with detrended *sc* (t-stat $= 2.30$ and 3.79 for FF25 and 100 portfolios, respectively) and negatively associated with *dfy* (t-stat $= -2.16$ and -3.98 for FF25 and 100 portfolios, respectively), exhibiting a strongly procyclical variation. Therefore, a procyclical time variation in the price of asset holders' consumption risk is observed for both the aggregate equity market portfolio and multiple equity portfolios.

Non-equity multiple asset classes. Another important question is whether this puzzling procyclical price of asset holders' consumption risk is also observed in non-equity multiple asset classes. Past studies demonstrate the importance of consumption for the cross-section of multiple asset classes (e.g., Bryzgalova and Julliard, 2021; Lustig and Verdelhan, 2007). Relatedly, Lettau et al. (2019) show that the capital share factor that proxies for wealthy households' consumption prices the cross-section of multi-asset classes. Therefore, we extend our analysis to multiple non-equity asset classes, specifically treasury and spread-sorted corporate bonds, basis-sorted commodity portfolios, and forward premium-sorted currency portfolios. For aggregate consumption, Panel A of Table 2 shows that the prices of aggregate consumption risk estimated using bonds and commodities are not significantly associated with the state variables. For asset holders' consumption, Panel B of Table 2 shows that the prices of asset holders' consumption risk from bonds and commodities exhibit a procyclical variation. For bonds, the price of asset holders' consumption risk is positively associated with detrended *sc* (t-stat = 4.07) and negatively associated with *dfy* (t-stat = −2.67). For commodities, the price of asset holders' consumption risk is negatively associated with *dfy* (t-stat = −3.07). For currencies, aggregate consumption generates a price of risk that varies countercyclically, as evidenced by its negative association with *sc* and positive association with *yc*. However, asset holders' consumption does not generate such a countercyclical price of risk. Rather, the prices of asset holders' consumption risk for currencies exhibit an acyclical variation.

Figure 3 plots the prices of risk, estimated using portfolios of multiple asset classes. The left panels of the figure show the prices of risk using NIPA aggregate consumption, and the right panels of the figure show the prices of risk using CEX asset holders' consumption.

We also plot detrended *sc* (red dashed line), *dfy* (black dotted line), and NBER recessions (shaded areas) to assess the dynamics of prices of risk. As in the regression results, the prices of aggregate consumption risk increase whenever there is a recession. The opposite pattern is observed for the prices of asset holders' consumption risk.

Overall, we find that the prices of asset holders' consumption risk exhibit a procyclical time variation. These dynamics hold for the aggregate equity market and multiple equity portfolios, and even for non-equity asset classes. These findings are puzzling, as existing consumption-based equilibrium asset pricing models do not predict such a time variation either endogenously or exogenously.

[Insert Figure 3 here]

4.1.2 Equity portfolios

In the previous test, we find that prices of asset holders' consumption risk that are estimated using Fama–French 25 size/book-to-market sorted portfolios (FF25) and 100 equity portfolios vary procyclically. Given the special focus on equities in the literature, we further examine the dynamics of the price of risk by re-estimating the prices of consumption risk separately using each of the four equity portfolio groups.

Panel A of Table 3 shows that although the overall NIPA aggregate consumption generates a countercyclical price of consumption risk, this countercyclical variation is only observed in two portfolio groups: 25 size/book-to-market portfolios and 100 equity portfolios. Panel B of Table 3 shows that the prices of asset holders' consumption risk estimated using a subset of 100 equity portfolios consistently exhibit a procyclical time variation. Prices of consumption risk estimated for the 25 size/book-to-market, the 25 size/investment, and

25 size/long-term reversal portfolios exhibit positive (negative) association with the procyclical (negative) state variables in a statistically significant way. For the size/operating profitability portfolios, both NIPA aggregate consumption and CEX asset holders' consumption produce prices of risk that are not significantly associated with the state variables.

In sum, our evidence suggests that the procyclical variation in the price of asset holders' consumption risk is consistently observed in different portfolios within the equity class.

[Insert Table 3 here]

4.2 Dynamics of consumption risk

We have identified the puzzling procyclical time variation in the prices of asset holders' consumption risk, which is robust to tests of multiple asset classes and multiple equity portfolios. To gain insight into the puzzling dynamics of the procyclical price of asset holders' consumption risk, we study the dynamics of the amount of consumption risk. Duffee (2005) finds a procyclical amount of aggregate consumption risk. As the equity risk premium is countercyclical, a procyclical amount of aggregate consumption risk requires a strongly countercyclical price of consumption risk to explain the countercyclical equity premium. Likewise, if the amount of asset holders' consumption risk exhibits a countercyclical variation more strongly than the countercyclicality of the equity premium, the price of asset holders' consumption risk may need to vary procyclically to fit the empirically observed countercyclical equity premium.

To examine this possibility, we regress the conditional amount of consumption risk for the aggregate equity market portfolio on the state variables. The first row of Table 4 shows that the signs on the coefficient of the state variables indicate a procyclical variation in the amount of aggregate consumption risk. The amount of aggregate consumption risk for the aggregate equity market portfolio is positively associated with (detrended) *sc* and negatively associated with *yc*. These signs are consistent with the composition effect first documented in Duffee (2005) – when stock market wealth is high relative to consumption, changes in aggregate consumption are more sensitive to changes in stock returns, leading to a high covariance in good states. However, the regression coefficients are statistically indistinguishable from zero, consistent with Xu (2021) which also documents the statistically insignificant procyclical variation in the amount of aggregate consumption risk using a different empirical methodology.[16]

The second row of Table 4 shows that when the amount of asset holders' consumption risk is regressed, the coefficients on the state variables take on the opposite sign to aggregate NIPA consumption, suggesting a countercyclical variation in the amount of asset holders' consumption risk.[17] However, different from the strongly cyclical price of asset holders' consumption risk, the amount of asset holders' consumption risk is only significantly associated with *yc* (t-stat = 4.27), but not with the other state variables.

Thus, it appears that the countercyclical variation in the amount of asset holders' consumption risk may to some extent contribute to the procyclical price of asset holders' risk. However, the amount of asset holders' consumption risk is only significantly associated with the labor–consumption ratio (*yc*). Thus, the empirical evidence seems not to be sufficient

[16]The difference between our finding and that of Duffee (2005) could be attributed to a few differences between the methodology used in this paper and the one used in Duffee (2005). For example, (1) we estimate the conditional amount of risk nonparametrically and (2) incorporate a large set of 162 financial and economic variables, and (3) our sample period includes a more recent sample period up to 2019.

[17]The countercyclical amount of consumption risk is consistent with leading representative-agent models (e.g., Campbell and Cochrane, 1999; Bekaert et al., 2009; Bekaert and Engstrom, 2017; Bollerslev et al., 2009; Bansal et al., 2009; Segal et al., 2015) and also a heterogeneous-agent model with market entry/exit (e.g., Elkamhi and Jo, 2021).

to conclude that the procyclical price of asset holders' consumption risk is fully attributable to the countercyclical amount of asset holders' consumption risk.

[Insert Table 4 here]

4.3 Re-assessment of value premium puzzle

Roussanov (2014) documents that value stocks tend to co-vary with aggregate consumption more than growth stocks during periods when financial wealth is low relative to consumption. However, the conditional value premium does not exhibit such a countercyclical time variation. We revisit the conditional value premium puzzle using asset holders' consumption. In doing so, we use the six Fama–French size/book-to-market sorted portfolios and separately examine the value premium within the small portfolio and the large portfolio as in Roussanov (2014).

Panel A of Table 5 shows the dynamics of the conditional value premium. Consistent with Roussanov (2014), the conditional value premium does not exhibit a countercyclical time variation. The signs on detrended *sc* and *sc* are positive, implying that the conditional value premium is high when financial wealth is high relative to consumption, although the coefficients are not precisely estimated. The most significant estimate is the negative association between conditional value premium in the small portfolio and *dfy* (t-stat $=$ -1.91), suggesting a procyclical time variation in the conditional value premium.

Panel B of Table 5 shows that the amount of aggregate consumption risk for the value-minus-growth long-short portfolios varies countercyclically, as documented in Roussanov (2014). In contrast, Panel C of Table 5 shows the opposite dynamics for asset holders' consumption: the amount of asset holders' consumption risk for the value-minus-growth portfolios varies procyclically, in the same direction as the conditional value premium.

Thus, we find evidence consistent with Roussanov (2014) using aggregate consumption. However, when asset holders' consumption is used, we show the amount of asset holders' consumption risk for the value-minus-growth portfolios varies in the same direction as the conditional value premium. Thus, we provide an explanation for the conditional value premium puzzle.

[Insert Table 5 here]

4.4 Pricing performances

In this subsection, we present the pricing performances of the conditional CCAPM using aggregate consumption and asset holders' consumption in explaining the dynamics of asset returns.

In assessing the performance of the model, we examine the estimates of the price of consumption risk (risk aversion) and pricing errors, as (1) the implied price of consumption risk estimates provide a direct economic measure of the plausibility of the model, and (2) other metrics such as pricing errors alone can be misleading as demonstrated in Lewellen et al. (2010). Table 6 reports the bottom 5% and top 5% of the implied price of consumption risk and the average pricing alphas ($\hat{\alpha}$ in Equations (9) and (11)). We also perform the hypothesis test that average pricing errors from aggregate consumption are the same as those from asset holders' consumption: $\hat{\alpha}_{agg} = \hat{\alpha}_{holder}$.[18]

Panel A of Table 6 presents the pricing performances using NIPA aggregate consumption. The price of aggregate consumption risk using the CRSP aggregate equity market portfolio ranges from −462.38 to −0.44, suggesting that expected returns are mostly negatively associated with the amount of aggregate consumption risk. This finding is in line with Duffee (2005), who documents that the interquartile range of the price of consumption risk ranges from −4 to −88 (−91 to 1) using surplus consumption (consumption-wealth ratio) as a single variable in z_t. In contrast, Panel B shows the price of asset holders' consumption risk using the CRSP aggregate equity market portfolio ranges from 7.04 to 47.83. Similar patterns are observed in tests at the portfolio level. Notably, asset holders' consumption risk does not always generate a positive estimate of the price of risk. However, it produces price of risk estimates more plausible than those from the NIPA aggregate consumption.

One may suspect that the plausible estimates of the price of consumption risk implied by asset holders' consumption relative to NIPA aggregate consumption are because the CEX consumption is unfiltered, while NIPA aggregate consumption is filtered (Kroencke, 2017). Online Appendix Figure OA.4 plots the price of aggregate consumption risk using CEX aggregate consumption. Although CEX aggregate consumption is unfiltered, the levels of the

[18] Bootstrap simulations are performed by randomly drawing sample months with replacement 5,000 times, using the stationary bootstrap procedure introduced by Politis and Romano (1994) with the random block lengths drawn from a geometric distribution to ensure the stationarity of the resulting time-series. Specifically, blocks of asset returns, risk-free rates, and consumption measures (for both NIPA aggregate consumption and CEX asset holders' consumption) together are resampled randomly with replacement until the bootstrap sample size is equal to the number of real data observations. Next, we obtain an estimate of the pricing error for aggregate consumption and NIPA consumption and compute the estimate of the difference between the two average pricing errors. We repeat this procedure 5,000 times and construct the bootstrap distribution of the estimate of the difference between the two average pricing errors. The p-values for the two-sided test are computed using the bootstrap distributions of the estimate of the difference between the two average pricing errors centered at zero.

price of consumption risk, implied by CEX aggregate consumption, are similar to those calculated for the NIPA aggregate consumption: Using the CRSP aggregate equity market portfolio, the 90% confidence interval for NIPA aggregate consumption is -462.38 and -0.44, which are -243.60 and 685.77 for CEX aggregate consumption, and 7.04 and 47.83 for CEX asset holders' consumption. Using 100 equity portfolios, these values are -174.35 and 113.75 for NIPA aggregate consumption, -67.76 and 118.53 for CEX aggregate consumption, and -19.20 and 26.73 for CEX asset holders' consumption. Therefore, the relatively plausible estimates of the price of risk implied by CEX asset holders' consumption compared to the NIPA do not seem to merely come from the fact that the CEX data are unfiltered, and the NIPA is filtered because CEX aggregate consumption does not produce the levels of the price of risk as CEX asset holders' consumption. This suggests that the price of consumption risk (risk aversion) estimates, using CEX asset holders' consumption, that are much more plausible than those from NIPA aggregate consumption, are likely to be because asset holders' consumption is theoretically more relevant to asset pricing than aggregate consumption, not because the CEX data are unfiltered.

In terms of average pricing errors, the asset holders' consumption generates generally lower pricing errors than aggregate consumption. However, the difference in pricing errors is statistically significant only for the aggregate equity market.

Overall, we find evidence on the improvement of the performance of the conditional CCAPM using asset holders' consumption relative to aggregate consumption. Even though we find the price of consumption risk (risk aversion) estimates, using asset holders' consumption, that are much more plausible than those from aggregate consumption (e.g., 7.04 to 47.83 using asset holders' consumption versus -462.38 to -0.44 using aggregate consumption), the levels of the price of consumption risk is mostly outside of generally accepted levels. To achieve more reasonable values, one can use asset holders' consumption for multi-factor consumption-based asset pricing models, in a conditional test setting, such as the long-run risk models that include both the short-run risk component that is tested in our study as well as the long-run risk component or a consumption-based model augmented with an aggregate wealth growth factor as in Roussanov (2014). Since our focus is on the dynamics of the price of consumption risk instead of the levels of the price of consumption risk, we leave this exercise for future research.

[Insert Table 6 here]

4.5 Robustness

This subsection provides a battery of robustness tests that verify that our findings are robust to different consumption measures, an automatic selection of the bandwidth, an alternative specification for ex-post covariances, and imposing the theoretically consistent sign.

4.5.1 Analysis using CEX aggregate consumption

One potential concern about our findings is the possibility that the procyclical time variation in the price of asset holders' consumption risk could be driven by the different consumption data sources. That is, there could be something specific to the CEX that leads to the procyclical variation in the price of asset holders' consumption risk, in sharp contrast to the countercyclical price of aggregate consumption risk implied by NIPA aggregate consumption. If that is the case, the procyclical price of consumption risk may be observed even using aggregate consumption of CEX households.

To verify that this is not the case, we repeat the main analysis using CEX aggregate consumption that includes both asset holders and non-asset holders. Panel A of Table 7 shows that the prices of consumption risk implied by CEX aggregate consumption exhibit a countercyclical variation, as opposed to the procyclical variation in the prices of risk implied by CEX asset holders' consumption, which are presented above. For all of the portfolios, the prices of CEX aggregate consumption risk are negatively associated with the procyclical state variables (i.e., detrended *sc* and *sc*) and positively associated with the countercyclical state variables (i.e., *dfy* and *yc*). For bonds and commodities, while NIPA aggregate consumption does not produce the price of risk estimates that are significantly associated with the state variables, the prices of consumption risk implied by CEX aggregate consumption exhibit a significant countercyclical variation. The price of CEX aggregate consumption risk is marginally significantly associated with *sc* (t-stat $= -1.86$) for bond portfolios and highly significantly associated with detrended *sc* (t-stat $= -3.71$), *sc* (t-stat $= -4.31$), and *yc* (t-stat $= 3.90$) for commodities.

Therefore, we find the countercyclical dynamics of the price of risk implied by CEX aggregate consumption versus the procyclical dynamics implied by CEX asset holders' consumption. These findings confirm that our results are not driven by the different data sources.

[Insert Table 7 here]

4.5.2 Out-of-sample validation using NielsenIQ data

Although the CEX data are widely used to measure micro-level consumption of asset holders (e.g., Brav et al., 2002; Paiella, 2004; Balduzzi and Yao, 2007; Malloy et al., 2009), measurement errors in the CEX data are well known (e.g., Aguiar and Bils, 2015; Lettau et al., 2019). Thus, we perform an out-of-sample validation using an alternative consumption data set to gauge the robustness of our key findings. For this exercise, we use the Consumer Panel Dataset (CPD) provided by the Kilts-Nielsen Data Center for the 2004 to 2019 period. As discussed in Subsection 3.2.2, to measure asset holders' consumption, we aggregate the consumption of households who reside in a county where dividend income to adjusted gross income is in the top 10% each year among US counties.

Panel B of Table 7 shows that NielsenIQ aggregate consumption produces the price of risk for the CRSP aggregate equity market portfolio that is negatively associated with detrended *sc* (t-stat = −3.81) and *sc* (t-stat = −4.92) and positively associated with *dfy* (t-stat = 15.23). Therefore, NielsenIQ aggregate produces the countercyclical price of consumption risk for the CRSP aggregate equity market portfolio. In contrast, Panel C shows that NielsenIQ asset holders' consumption produces the price of consumption risk for the CRSP aggregate equity market portfolio that is positively associated with detrended *sc* (t-stat = 3.46) and *sc* (t-stat = 2.51) and negatively associated with *yc* (t-stat = −10.89), exhibiting a procyclical price of asset holders' consumption risk.

The prices of asset holders' consumption risk are still observed in multiple portfolios, although the associations with the state variables are less significant than the ones using the CEX, possibly due to the shorter sample period in the NielsenIQ than the CEX. For example, the prices of asset holders' consumption risk using FF25 portfolios and bond portfolios are significantly and negatively associated with *dfy* (t-stat = -2.83 and t-stat = -2.10, respectively). They are weakly and positively correlated with *sc* (t-stat = 1.96 and t-stat = 1.70, respectively). For commodities, the prices of asset holders' consumption risk exhibit strong procyclical variation based on all of the four state variables. For currencies, different from the previous results based on the NIPA and the CEX, both aggregate consumption and asset holders' consumption generate a countercyclical variation in the price of consumption risk.

Overall, our empirical evidence from this alternative consumption data set suggests that our key findings are largely robust to NielsenIQ CPD consumption data, albeit less significantly than before – the CRSP aggregate equity market portfolio, FF25 portfolios, bonds, and commodities imply the procyclical price of asset holders' consumption risk.

4.5.3 Different bandwidth selection

Our nonparametric estimation relies on the bias-corrected Akaike Information Criterion (Hurvich et al., 1998) to automatically select the bandwidth. In this subsection, we repeat our main analysis using the generalized cross-validation (Craven and Wahba, 1978) which is another approach to selecting the bandwidth. Table 8 presents the main analysis of the dynamics of the price of risk using multi-asset classes, based on the generalized cross-validation. The results show that the price of consumption risk implied by asset holders' consumption varies procyclically, while NIPA aggregate consumption generates the opposite dynamics. Our estimates of the regression coefficients and significance level are highly similar to those in Table 2, suggesting that our main results are robust to this alternative bandwidth selection approach quantitatively and qualitatively.

[Insert Table 8 here]

4.5.4 Different specification for Ex-post covariances

In our tests, we use the first three principal components of the 162 state variables (z_t) to compute the residuals of consumption growth and asset returns, which in turn are used to construct ex-post covariances. In this subsection, we conduct a robustness test by removing a set of conditioning variables z_t from our construction of the ex-post covariances. This could lead to misspecification if part of the investors' information is in the omitted set of conditioning variables. Nonetheless, this exercise provides a sense of how sensitive our main findings are with respect to a different specification to compute ex-post covariances. Table 9 presents the main analysis of the dynamics of the price of risk using multi-asset classes, based on this alternative specification that omits a set of conditioning variables z_t. The results show that our main results are largely robust to the alternative specification. Panel A shows that the prices of consumption risk estimated using the NIPA aggregate consumption are negatively correlated with detrended *sc*, except for commodities. In contrast, Panel B shows that the prices of consumption risk for CEX asset holders are strongly positively correlated with detrended *sc*. They are always significant at the 5% level except for currencies. A similar pattern is observed for *dfy* – the prices of asset holders' consumption risk are always significant at the 1% level with a negative sign, except for currencies. For currencies, as before, while aggregate consumption implies a strongly countercyclical price of consumption risk, asset holders' consumption risk implies an acyclical price of consumption risk.

Overall, our robustness test results imply that our main findings are not sensitive to the omission of the set of conditioning variables z_t in the construction of ex-post covariances.

[Insert Table 9 here]

4.5.5 Imposing the theoretically consistent sign

One limitation of our empirical approach is that there could be a negative value of the estimated conditional excess returns. This is not consistent with theories because it implies a negative risk premium. To address this limitation, we impose the conditional expectation of excess returns to be zero whenever it is negative as in Campbell and Thompson (2008).[19]

Table 10 presents the main analysis of the dynamics of the price of risk using multi-asset classes by imposing such a restriction. We omit the test using the CRSP aggregate equity market portfolio since this test does not rely on the estimation of conditional excess returns. The results show that our main results are robust to imposing the theoretically consistent sign. NIPA aggregate consumption generates a countercyclical price of consumption risk, and CEX asset holders generate a procyclical price of consumption risk. This suggests that the issue of negative conditional expected returns does not significantly drive our findings.

[Insert Table 10 here]

5 Conclusion

In this article, we identify a puzzling time variation in the price of asset holders' consumption risk. We find that the prices of asset holders' consumption risk vary procyclically, whereas the prices of aggregate consumption risk vary countercyclically. These findings are salient empirical facts that are robust to multiple asset classes – the aggregate equity market portfolio, equity portfolios, bond portfolios, and commodities. This finding is not specific to the CEX data for the following reasons: (1) Aggregate consumption using CEX data

[19] Campbell and Thompson (2008) set the equity premium forecast to zero whenever it is negative to predict returns on the S&P 500 index.

does not generate a procyclical price of consumption risk, but rather generates a strongly countercyclical price of consumption risk, as in the NIPA aggregate consumption. (2) Our findings also hold for an alternative micro-level high-frequency retail shopping data set, the NielsenIQ Consumer Panel Data.

Our findings sharply contrast with major consumption-based equilibrium asset pricing models in which the price of consumption risk is either constant or countercyclical (habit formation models/heterogeneous agent models with fixed participation). One possible explanation for the procyclical price of asset holders' consumption risk is asset holders' entry and exit with heterogeneous risk aversion as in Elkamhi and Jo (2021). In bad states, if only risk-tolerant investors remain in asset markets after the exits of risk-averse investors, the risk aversion of average market participants is low (low price of risk). In good states, even risk-averse investors participate in risky asset investments, raising the risk aversion of average market participants (high price of risk), leading to a procyclical price of risk. This economic mechanism may explain our puzzling empirical evidence. However, a further thorough analysis is needed to conclude that this is indeed the key mechanism that explains our puzzling empirical findings. We leave it for future research.

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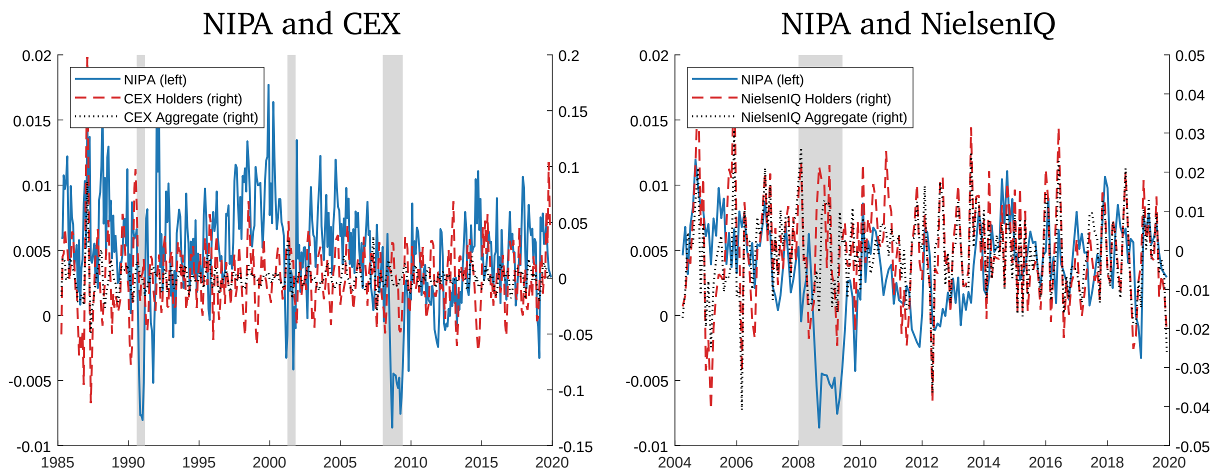

Figure 1. **Consumption Measures**

This figure plots a time series of three-month growth rates of consumption measures. The left panel of the figure displays NIPA aggregate consumption, aggregate consumption from the national income and product accounts (NIPA) by the Bureau of Economic Analysis (blue solid line), CEX asset holders' consumption, the consumption of households who have a positive financial asset from the data of the Consumer Expenditure Survey by the Bureau of Labor Statistics (red dashed line), and CEX aggregate consumption, aggregate consumption in the CEX data (black dotted line). 3-month moving averages are displayed for CEX consumption measures for exposition. The right panel of the figure displays NIPA aggregate consumption (blue solid line), NielsenIQ asset holders' consumption, the consumption of households who reside in a county where dividend income to adjusted gross income is in the top 10% from the consumer panel data by NielsenIQ (red dashed line), NielsenIQ aggregate consumption, aggregate consumption from the consumer panel data by NielsenIQ (black dotted line). Shaded areas denote the NBER recessions.

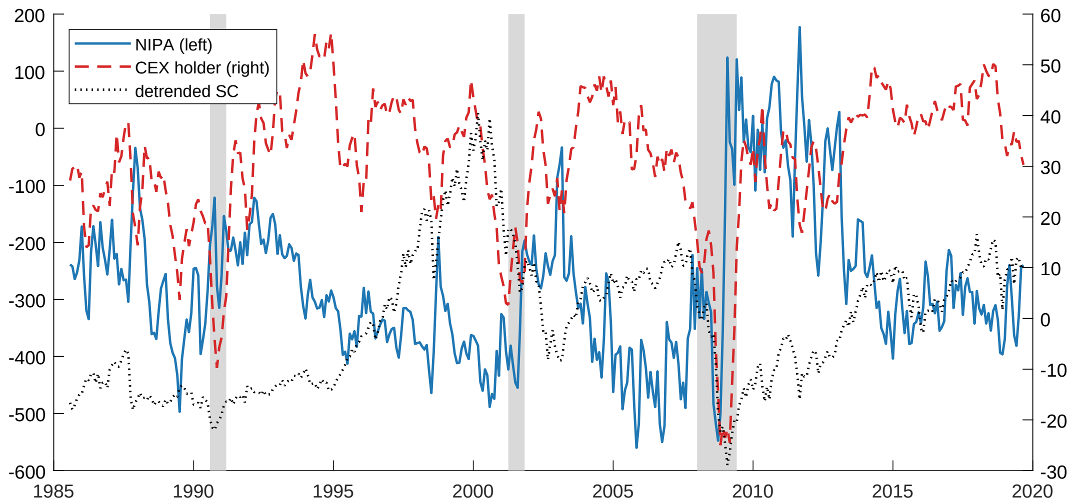

Figure 2. **Conditional Price of Consumption risk using Aggregate market**

This figure plots the conditional price of consumption risk, $\hat{\gamma}_t$ estimated using the CRSP Equity market portfolio and the linear time-series regression: $R^e_{t+1} = \alpha + (\gamma_0 + \gamma_1' z_t)\widehat{Cov}_t(R^e_{t+1}, \Delta C_{t+1}/C_t) + \epsilon_{t+1}$ where $\hat{\gamma}_t = \hat{\gamma}_0 + \hat{\gamma}_1' z_t$ and z_t is a set of conditioning variables. The blue solid line is the price of consumption risk using NIPA aggregate consumption. The red dashed line is the price of consumption risk using CEX asset holders' consumption. The black dotted line is the detrended stock market wealth-to-aggregate consumption ratio. Shaded areas denote the NBER recessions.

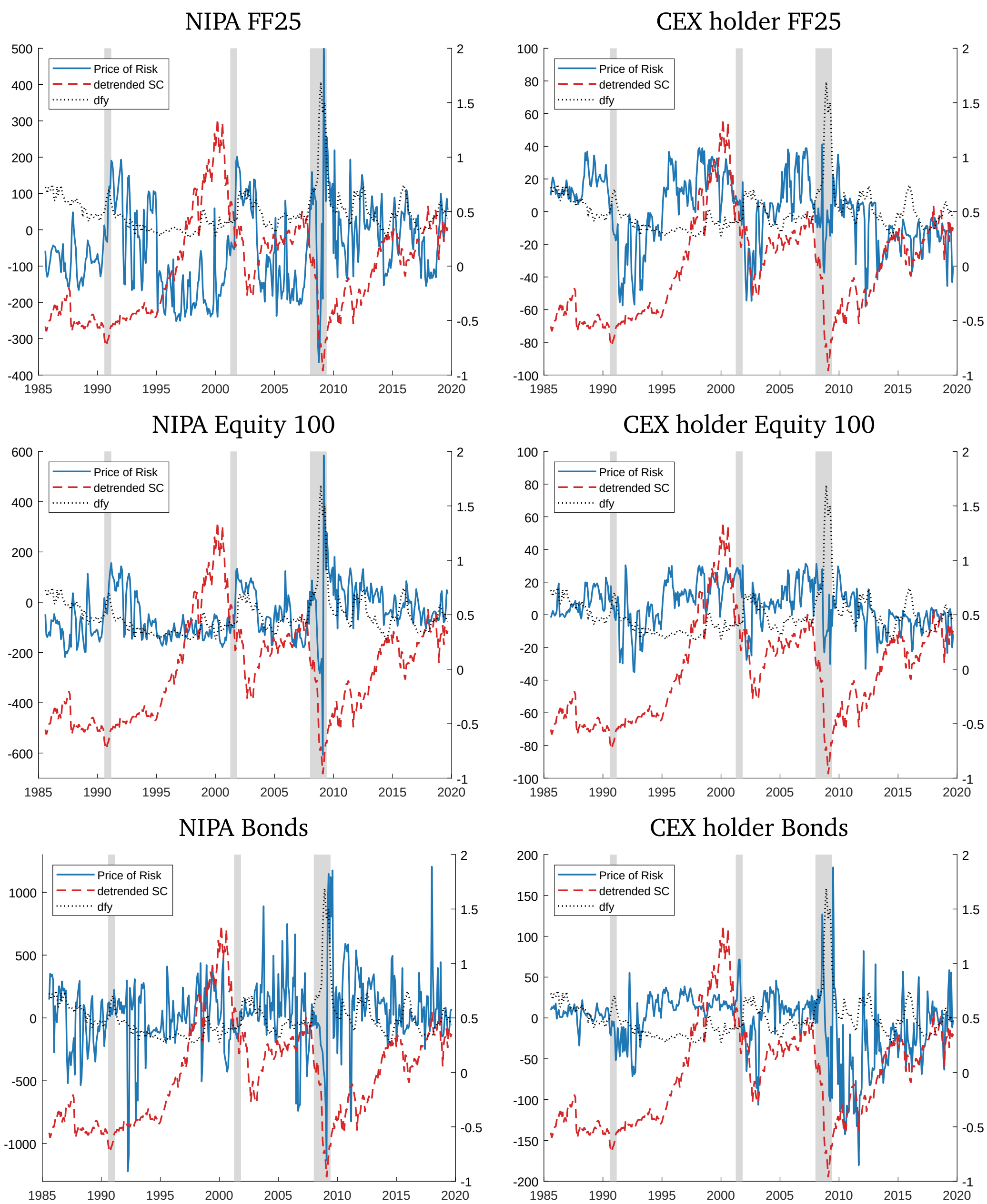

Figure 3. **Conditional Price of Consumption risk for Each Portfolio Group**

This figure plots the conditional price of consumption risk estimated using each portfolio group. The left (right) panels of the figure display the prices of consumption risk using NIPA aggregate (CEX asset holders') consumption. The price of consumption risk is estimated using the cross-sectional nonparametric estimation by Roussanov (2014): $\hat{\gamma}_t = (\hat{\mathbf{cv}}_t' W \hat{\mathbf{cv}}_t)^{-1} \hat{\mathbf{cv}}_t' W \hat{\mathbf{m}}_t$ where $\hat{\mathbf{cv}}_t$ is $N \times 2$ vector of ones and nonparametrically estimated conditional covariances, W is the weighting matrix, and $\hat{\mathbf{m}}_t$ is $N \times 1$ vector of nonparametrically estimated conditional expectation of excess returns. The blue solid line is the price of consumption risk. The red dashed line is the detrended stock market wealth-to-aggregate consumption ratio (detrended sc). The black dotted line is the default yield spread (dfy), the difference between BAA and AAA-rated corporate bond yields. Shaded areas denote the NBER recessions.

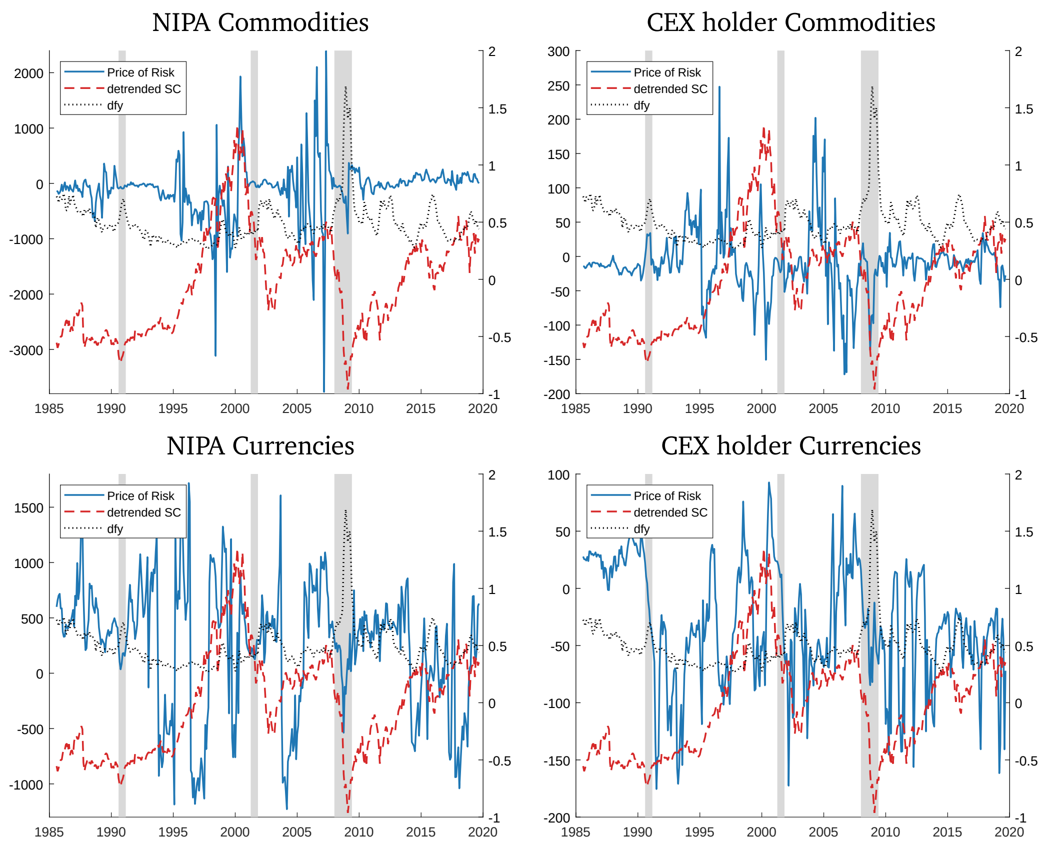

Figure 3. **Conditional Price of Consumption risk for Each Portfolio Group (Cont'd).**

Table 1. **Summary Statistics**

This table reports the summary statistics of 3-month returns on test assets (Panel A) and 3-month consumption growth (Panel B), respectively. CRSP Equity Market is the CRSP value-weighted equity market index. Equity - FF25 portfolios is 25 size/book-to-market sorted portfolios. Equity - 100 portfolios is 25 size/book-to-market, 25 size/investment, 25 size/operating profitability, and 25 size/long-term reversal sorted portfolios. Bonds is 10 credit spread-sorted corporate bond portfolios (Nozawa, 2017) and 8 Treasury bonds. Commodities is 5 basis-sorted commodity portfolios (Yang, 2013). Currencies is 6 portfolios sorted on forward premiums (Lettau et al., 2014). NIPA Aggregate is NIPA aggregate consumption by the Bureau of Economic Analysis. CEX Asset holders is the consumption of households who have a positive financial asset from the data of the Consumer Expenditure Survey by the Bureau of Labor Statistics. CEX Aggregate is aggregate consumption in the CEX data. NielsenIQ Asset holders is the consumption of households who reside in a county where dividend income to adjusted gross income is in the top 10% from the consumer panel data by NielsenIQ. NielsenIQ Aggregate is consumption from the consumer panel data by NielsenIQ that aggregates consumption of all households.

			Percentiles (%)				
	Mean (%)	Std (%)	1st	10th	50th	90th	99th
Panel A: Test assets							
CRSP Equity Market	2.92	7.82	-23.31	-6.44	3.82	11.35	20.64
Equity - FF25 portfolios	3.27	10.12	-27.82	-8.62	4.05	14.39	26.47
Equity - 100 portfolios	3.32	9.88	-27.36	-8.12	4.02	14.23	26.05
Bonds	1.85	3.77	-7.84	-1.77	1.54	5.81	12.16
Commodities	1.33	9.23	-22.3	-9.11	1.05	12.28	25.04
Currencies	1.77	4.49	-9.04	-3.3	1.57	7.34	13.16
Panel B: Consumption measures							
NIPA Aggregate	0.49	0.42	-0.76	-0.03	0.52	1.00	1.51
CEX Asset holders	0.07	5.00	-12.05	-5.60	-0.18	6.39	15.04
CEX Aggregate	0.02	1.59	-3.76	-1.60	-0.06	1.68	4.22
NielsenIQ Asset holders	-0.01	1.41	-3.58	-1.73	-0.17	1.82	3.87
NielsenIQ Aggregate	-0.07	1.10	-3.24	-1.35	0.01	1.24	2.58

Table 2. **Dynamics of Price of Consumption Risk using Multi-Asset Classes**

This table presents the dynamics of the price of consumption risk for the aggregate equity portfolio and multiple asset classes using NIPA aggregate consumption and CEX asset holders' consumption based on a regression of the following equation: $\hat{\gamma}_t = a+\beta X_t+\epsilon_t$ where $\hat{\gamma}_t$ is the price of consumption risk estimated by the cross-sectional nonparametric estimation in Roussanov (2014) using N assets: $[\hat{\alpha}_t \;\; \hat{\gamma}_t]' = (\hat{\mathbf{cv}}_t' W \hat{\mathbf{cv}}_t)^{-1}\hat{\mathbf{cv}}_t' W \hat{\mathbf{m}}_t$ where $\hat{\mathbf{cv}}_t$ is $N\times 2$ vector of ones and nonparametrically estimated conditional covariances, W is the weighting matrix, and $\hat{\mathbf{m}}_t$ is $N \times 1$ vector of nonparametrically estimated conditional expectation of excess returns. For the CRSP Equity market portfolio ($N = 1$), the price of risk is estimated using the linear time-series regression: $R^e_{m,t+1} = \alpha+(\gamma_0+\gamma_1' z_t)\widehat{Cov}_t(R^e_{t+1}, \Delta C_{t+1}/C_t)+\epsilon_{t+1}$ where $\hat{\gamma}_t = \hat{\gamma}_0+\hat{\gamma}_1' z_t$ and z_t is a set of conditioning variables. X_t is a state variable that is standardized to a unit standard deviation – sc (Stock market wealth-to-aggregate consumption ratio), detrended sc, dfy (default yield spread, the difference between BAA and AAA-rated corporate bond yields), and yc (labor income-to-aggregate consumption ratio). NIPA Aggregate is NIPA aggregate consumption by the Bureau of Economic Analysis. CEX asset holder is the consumption of households who have a positive financial asset from the data of the Consumer Expenditure Survey by the Bureau of Labor Statistics. CRSP Equity Market is the CRSP value-weighted equity market index. Equity - FF25 portfolios is 25 size/book-to-market sorted portfolios. Equity - 100 portfolios is 25 size/book-to-market, 25 size/investment, 25 size/operating profitability, and 25 size/long-term reversal sorted portfolios. Bonds is 10 credit spread-sorted corporate bond portfolios (Nozawa, 2017) and 8 Treasury bonds. Commodities is 5 basis-sorted commodity portfolios (Yang, 2013). Currencies is 6 portfolios sorted on forward premiums (Lettau et al., 2014). ***,**,* denote the statistical significance at 1%, 5%, and 10%, respectively, based on the Hansen and Hodrick (1980) with three months lag.

	detrended sc		sc		dfy		yc	
	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat
Panel A: NIPA Aggregate								
CRSP Equity Market	-67.71	-7.40***	-45.41	-5.75***	40.65	2.40**	38.73	4.98***
Equity - FF25 portfolios	-40.58	-4.72***	-21.38	-2.44**	33.12	1.76*	13.23	1.54
Equity - 100 portfolios	-20.12	-2.36**	-2.54	-0.33	16.45	0.88	-0.33	-0.04
Bonds	1.75	0.07	21.42	1.11	12.82	0.30	-21.01	-1.04
Commodities	-28.72	-0.56	14.44	0.39	41.03	1.12	-17.71	-0.48
Currencies	-72.01	-1.55	-109.40	-2.54**	66.94	1.18	116.94	2.8***
Panel B: CEX Asset holders								
CRSP Equity Market	4.45	2.94***	4.52	3.72***	-8.95	-13.44***	-2.47	-2.18**
Equity - FF25 portfolios	4.09	2.30**	0.22	0.11	-2.73	-2.16**	-0.45	-0.23
Equity - 100 portfolios	3.71	3.79***	1.68	1.53	-2.91	-3.98***	-1.84	-1.79*
Bonds	9.98	4.07***	2.60	1.22	-8.10	-2.67***	-2.11	-1.02
Commodities	-4.80	-1.22	-4.35	-1.33	-9.97	-3.07***	4.06	1.08
Currencies	1.39	0.28	-5.25	-1.06	4.10	0.98	5.31	1.04

Table 3. **Dynamics of Price of Consumption Risk using Equity Portfolios**

This table presents the dynamics of the price of consumption risk for multiple equity portfolios using NIPA aggregate consumption and CEX asset holders' consumption based on a regression of the following equation: $\hat{\gamma}_t = a + \beta X_t + \epsilon_t$ where $\hat{\gamma}_t$ is the price of consumption risk estimated by the cross-sectional nonparametric estimation in Roussanov (2014) using N assets: $[\hat{\alpha}_t \;\; \hat{\gamma}_t]' = (\hat{\mathbf{cv}}_t' W \hat{\mathbf{cv}}_t)^{-1} \hat{\mathbf{cv}}_t' W \hat{\mathbf{m}}_t$ where $\hat{\mathbf{cv}}_t$ is $N \times 2$ vector of ones and nonparametrically estimated conditional covariances, W is the weighting matrix, and $\hat{\mathbf{m}}_t$ is $N \times 1$ vector of nonparametrically estimated conditional expectation of excess returns. X_t is a state variable that is standardized to a unit standard deviation – sc (Stock market wealth-to-aggregate consumption ratio), detrended sc, dfy (default yield spread, the difference between BAA and AAA-rated corporate bond yields), and yc (labor income-to-aggregate consumption ratio). NIPA Aggregate is NIPA aggregate consumption by the Bureau of Economic Analysis. CEX asset holder is the consumption of households who have a positive financial asset from the data of the Consumer Expenditure Survey by the Bureau of Labor Statistics. Size/BM is 25 size/book-to-market sorted portfolios. Size/INV is 25 size/investment sorted portfolio. Size/OP is 25 size/operating profitability portfolios. Size/REV is 25 size/long-term reversal portfolios. All Equities are 100 portfolios of Size/BM, Size/INV, Size/OP, and Size/REV. ***,**,* denote the statistical significance at 1%, 5%, and 10%, respectively, based on the Hansen and Hodrick (1980) with three months lag.

	detrended sc		sc		dfy		yc	
	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat
Panel A: NIPA Aggregate								
Size/BM 25 portfolios	-40.58	-4.72***	-21.38	-2.44**	33.12	1.76*	13.23	1.54
Size/INV 25 portfolios	-14.17	-1.24	9.10	0.90	7.82	0.40	-13.19	-1.35
Size/OP 25 portfolios	-13.46	-1.43	6.39	0.75	9.91	0.54	-3.78	-0.47
Size/REV 25 portfolios	5.88	0.51	7.11	0.74	3.34	0.14	-7.02	-0.75
All Equities	-20.12	-2.36**	-2.54	-0.33	16.45	0.88	-0.33	-0.04
Panel B: CEX Asset holders								
Size/BM 25 portfolios	4.09	2.30**	0.22	0.11	-2.73	-2.16**	-0.45	-0.23
Size/INV 25 portfolios	3.45	2.73***	1.63	1.24	-2.25	-2.66***	-2.65	-2.13**
Size/OP 25 portfolios	1.30	0.91	-0.29	-0.20	-1.17	-0.72	0.05	0.03
Size/REV 25 portfolios	3.37	3.92***	2.71	3.15***	-3.14	-4.15***	-1.78	-2.05**
All Equities	3.71	3.79***	1.68	1.53	-2.91	-3.98***	-1.84	-1.79*

Table 4. **Dynamics of Amount of Consumption Risk**

This table presents the dynamics of the amount of consumption risk based on a regression of the following equation: $\widehat{Cov}_t(R^e_{t+1}, \Delta C_{t+1}/C_t) = a + \beta X_t + \epsilon_t$ where $\widehat{Cov}_t(R^e_{t+1}, \Delta C_{t+1}/C_t)$ is the conditional covariances between consumption growth and CRSP Equity market returns nonparametrically estimated. X_t is a state variable that is standardized to a unit standard deviation – sc (Stock market wealth-to-aggregate consumption ratio), detrended sc, dfy (default yield spread, the difference between BAA and AAA-rated corporate bond yields), and yc (labor income-to-aggregate consumption ratio). NIPA Aggregate is NIPA aggregate consumption by the Bureau of Economic Analysis. CEX asset holder is the consumption of households who have a positive financial asset from the data of the Consumer Expenditure Survey by the Bureau of Labor Statistics. ***,**,* denote the statistical significance at 1%, 5%, and 10%, respectively, based on the Hansen and Hodrick (1980) with three months lag.

	detrended sc		sc		dfy		yc	
	$\hat{\beta} \times 10^5$	t-stat	$\hat{\beta} \times 10^5$	t-stat	$\hat{\beta} \times 10^5$	t-stat	$\hat{\beta} \times 10^5$	t-stat
NIPA Aggregate	0.21	0.35	0.23	0.47	1.47	1.20	-0.46	-0.64
CEX Asset holders	-0.64	-0.07	-5.97	-0.97	-14.45	-0.81	15.85	4.27***

Table 5. **Re-assessment of Value Premium Puzzle**

This table presents the dynamics of the conditional value premium, its exposure to aggregate consumption risk, and asset holders' consumption risk based on a regression of the following equations: $\hat{R}_{V,i,t} - \hat{R}_{G,i,t} = a + \beta X_t + \epsilon_t$ and $\widehat{Cov}_t(R_{V,i,t+1} - R_{G,i,t+1}, \Delta C_{t+1}/C_t) = a + \beta X_t + \epsilon_t$, using 6 size/book-to-market sorted portfolios, where $\hat{R}_{V,i,t} - \hat{R}_{G,i,t}$ is the conditional value premium within small ($i = S$) or large ($i = L$) size portfolios that is estimated nonparametrically. X_t is a state variable that is standardized to a unit standard deviation – sc (Stock market wealth-to-aggregate consumption ratio), detrended sc, dfy (default yield spread, the difference between BAA and AAA-rated corporate bond yields), and yc (labor income-to-aggregate consumption ratio). NIPA Aggregate is NIPA aggregate consumption by the Bureau of Economic Analysis. CEX asset holder is the consumption of households who have a positive financial asset from the data of the Consumer Expenditure Survey by the Bureau of Labor Statistics. CEX Aggregate is aggregate consumption in the CEX data. Size/BM is 25 size/book-to-market sorted portfolios. Size/INV is 25 size/investment sorted portfolio. Size/OP is 25 size/operating profitability portfolios. Size/REV is 25 size/long-term reversal portfolios. All Equities are 100 portfolios of Size/BM, Size/INV, Size/OP, and Size/REV. ***,**,* denote the statistical significance at 1%, 5%, and 10%, respectively, based on the Hansen and Hodrick (1980) with three months lag.

	detrended sc		sc		dfy		yc	
	$\hat{\beta} \times 10^4$	t-stat	$\hat{\beta} \times 10^4$	t-stat	$\hat{\beta} \times 10^4$	t-stat	$\hat{\beta} \times 10^4$	t-stat
Panel A: Returns dynamics								
Return of SV-SG	19.23	1.34	3.28	0.32	-57.61	-1.91*	3.96	0.44
Return of LV-LG	19.74	0.81	9.20	0.65	-34.57	-0.48	-2.39	-0.15
Panel B: NIPA Aggregate								
Cov of SV-SG	-0.13	-2.52**	-0.02	-0.50	0.16	2.73***	-0.05	-1.11
Cov of LV-LG	-0.11	-1.90*	-0.01	-0.26	0.22	2.16**	-0.10	-2.13**
Panel C: CEX Asset holder								
Cov of SV-SG	0.75	1.16	0.92	2.23**	1.31	0.76	-0.99	-3.02***
Cov of LV-LG	1.60	1.71*	1.97	3.34***	0.05	0.02	-1.52	-3.68***

Table 6. **Pricing Performance using Multi-Asset Classes**

This table reports the bottom 5% and top 5% of the implied price of consumption risk as well as average pricing alphas and their bottom 5% and top 5% of the bootstrap distribution. For multiple portfolios, the price of consumption risk is estimated by the cross-sectional nonparametric estimation in Roussanov (2014) using N assets: $[\hat{\alpha}_t \;\; \hat{\gamma}_t]' = (\hat{\mathbf{cv}}_t' W \hat{\mathbf{cv}}_t)^{-1} \hat{\mathbf{cv}}_t' W \hat{\mathbf{m}}_t$ where $\hat{\mathbf{cv}}_t$ is $N \times 2$ vector of ones and nonparametrically estimated conditional covariances, W is the weighting matrix, and $\hat{\mathbf{m}}_t$ is $N \times 1$ vector of nonparametrically estimated conditional expectation of excess returns. For the CRSP Equity market portfolio ($N = 1$), the price of risk is estimated using the linear time-series regression: $R^e_{m,t+1} = \alpha + (\gamma_0 + \gamma_1' z_t)\widehat{Cov}_t(R^e_{t+1}, \Delta C_{t+1}/C_t) + \epsilon_{t+1}$ where $\hat{\gamma}_t = \hat{\gamma}_0 + \hat{\gamma}_1' z_t$ and z_t is a set of conditioning variables. NIPA Aggregate is NIPA aggregate consumption by the Bureau of Economic Analysis. CEX asset holder is the consumption of households who have a positive financial asset from the data of the Consumer Expenditure Survey by the Bureau of Labor Statistics. CRSP Equity Market is the CRSP value-weighted equity market index. Equity - FF25 portfolios is 25 size/book-to-market sorted portfolios. Equity - 100 portfolios is 25 size/book-to-market, 25 size/investment, 25 size/operating profitability, and 25 size/long-term reversal sorted portfolios. Bonds is 10 credit spread-sorted corporate bond portfolios (Nozawa, 2017) and 8 Treasury bonds. Commodities is 5 basis-sorted commodity portfolios (Yang, 2013). Currencies is 6 portfolios sorted on forward premiums (Lettau et al., 2014).

	Risk aversion		Pricing errors (%)			
	$\hat{\gamma}$-Low	$\hat{\gamma}$-High	$\hat{\alpha}$	$\hat{\alpha}$-Low	$\hat{\alpha}$-High	P-value of $H_0 : \hat{\alpha}_{agg} = \hat{\alpha}_{holder}$
			Panel A: NIPA Aggregate			
CRSP Equity Market	-462.38	-0.44	4.12	2.33	4.61	0.01
Equity - FF25 portfolios	-227.08	144.46	2.74	2.04	3.50	0.72
Equity - 100 portfolios	-174.35	113.75	2.88	2.24	3.45	0.66
Bonds	-428.03	465.40	0.83	0.68	1.00	0.82
Commodities	-918.23	513.14	0.03	-0.42	0.79	0.33
Currencies	-905.88	1,048.44	0.70	-0.06	1.41	0.77
			Panel B: CEX Asset holders			
CRSP Equity Market	7.04	47.83	1.76	0.92	2.77	
Equity - FF25 portfolios	-40.71	33.04	2.61	2.20	3.11	
Equity - 100 portfolios	-19.20	26.73	2.73	2.26	3.14	
Bonds	-85.69	35.30	0.80	0.60	0.95	
Commodities	-84.90	65.89	-0.38	-1.57	0.51	
Currencies	-127.07	41.16	0.58	0.29	1.02	

Table 7. **Robustness 1: Different Sources of Consumption**

This table presents the dynamics of the price of consumption risk for the aggregate equity portfolio and multiple asset classes using CEX aggregate consumption and NielsenIQ consumption measures based on a regression of the following equation: $\hat{\gamma}_t = a + \beta X_t + \epsilon_t$ where $\hat{\gamma}_t$ is the price of consumption risk estimated by the cross-sectional nonparametric estimation in Roussanov (2014) using N assets: $[\hat{\alpha}_t \;\; \hat{\gamma}_t]' = (\hat{\mathbf{cv}}_t' W \hat{\mathbf{cv}}_t)^{-1} \hat{\mathbf{cv}}_t' W \hat{\mathbf{m}}_t$ where $\hat{\mathbf{cv}}_t$ is $N \times 2$ vector of ones and nonparametrically estimated conditional covariances, W is the weighting matrix, and $\hat{\mathbf{m}}_t$ is $N \times 1$ vector of nonparametrically estimated conditional expectation of excess returns. For the CRSP Equity market portfolio ($N = 1$), the price of risk is estimated using the linear time-series regression: $R^e_{t+1} = \alpha + (\gamma_0 + \gamma_1' z_t)\widehat{Cov}_t(R^e_{t+1}, \Delta C_{t+1}/C_t) + \epsilon_{t+1}$ where $\hat{\gamma}_t = \hat{\gamma}_0 + \hat{\gamma}_1' z_t$ and z_t is a set of conditioning variables. X_t is a state variable that is standardized to a unit standard deviation – sc (Stock market wealth-to-aggregate consumption ratio), detrended sc, dfy (default yield spread, the difference between BAA and AAA-rated corporate bond yields), and yc (labor income-to-aggregate consumption ratio). CEX Aggregate is aggregate consumption from the Consumer Expenditure Survey by the Bureau of Labor Statistics (Panel A). NielsenIQ Aggregate is consumption from the consumer panel data by NielsenIQ that aggregate consumption of all households (Panel B). NielsenIQ asset holder is the consumption of households who reside in a county where dividend income to adjusted gross income is in the top 10% from the consumer panel data by NielsenIQ (Panel C). CRSP Equity Market is the CRSP value-weighted equity market index. Equity - FF25 portfolios is 25 size/book-to-market sorted portfolios. Equity - 100 portfolios is 25 size/book-to-market, 25 size/investment, 25 size/operating profitability, and 25 size/long-term reversal sorted portfolios. Bonds is 10 credit spread-sorted corporate bond portfolios (Nozawa, 2017) and 8 Treasury bonds. Commodities is 5 basis-sorted commodity portfolios (Yang, 2013). Currencies is 6 portfolios sorted on forward premiums (Lettau et al., 2014). ***,**,* denote the statistical significance at 1%, 5%, and 10%, respectively, based on the Hansen and Hodrick (1980) with three months lag.

	detrended sc		sc		dfy		yc	
	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat
Panel A: CEX Aggregate								
CRSP Equity Market	-109.72	-3.11***	-101.17	-3.65***	218.78	14.37***	51.36	2.01**
Equity - FF25 portfolios	-7.60	-1.67*	-11.95	-3.40***	7.66	0.87	11.71	2.80***
Equity - 100 portfolios	-6.12	-1.52	-9.31	-2.76***	7.12	1.11	6.27	1.51
Bonds	-3.33	-0.18	-27.66	-1.86*	21.86	0.85	9.31	0.71
Commodities	-28.46	-3.71***	-25.42	-4.31***	9.68	0.56	28.48	3.90***
Currencies	-31.96	-2.40**	-50.27	-4.50***	9.21	0.45	55.22	4.99***
Panel B: NielsenIQ Aggregate								
CRSP Equity Market	-82.62	-3.81***	-95.51	-4.92***	108.14	15.23***	-15.36	-0.98
Equity - FF25 portfolios	0.75	0.13	5.10	0.93	-6.01	-1.03	6.44	1.46
Equity - 100 portfolios	-15.63	-1.91*	-14.11	-1.81*	-0.61	-0.09	12.69	2.25**
Bonds	3.48	0.07	20.72	0.44	-63.34	-1.36	48.05	2.55**
Commodities	3.26	0.22	10.88	0.82	-25.37	-2.39**	16.96	1.82*
Currencies	-41.31	-3.28***	-41.11	-3.42***	17.41	1.35	25.96	1.70*
Panel C: NielsenIQ Asset holders								
CRSP Equity Market	51.78	3.46***	34.78	2.51**	-3.93	-0.28	-79.56	-10.89***
Equity - FF25 portfolios	6.23	1.17	9.20	1.96*	-12.18	-2.83***	6.35	1.60
Equity - 100 portfolios	-10.09	-1.57	-11.34	-1.80*	-1.96	-0.33	5.28	1.27
Bonds	45.92	1.51	49.58	1.70*	-64.52	-2.1**	-8.02	-0.65
Commodities	63.86	3.60***	47.60	2.53**	-61.03	-3.12***	-59.61	-3.37***
Currencies	-42.03	-2.67***	-39.04	-2.60**	11.34	0.90	31.70	3.25***

Table 8. **Robustness 2: Difference Selection Methods of Bandwidth**

This table presents the dynamics of the price of consumption risk, using the generalized cross-validation to automatically select the bandwidth (Craven and Wahba, 1978), for the aggregate equity portfolio and multiple asset classes using NIPA aggregate consumption and CEX asset holders' consumption based on a regression of the following equation: $\hat{\gamma}_t = a + \beta X_t + \epsilon_t$ where $\hat{\gamma}_t$ is the price of consumption risk estimated by the cross-sectional nonparametric estimation in Roussanov (2014) using N assets: $[\hat{\alpha}_t \;\; \hat{\gamma}_t]' = (\hat{\mathbf{cv}}_t' W \hat{\mathbf{cv}}_t)^{-1} \hat{\mathbf{cv}}_t' W \hat{\mathbf{m}}_t$ where $\hat{\mathbf{cv}}_t$ is $N\times2$ vector of ones and nonparametrically estimated conditional covariances, W is the weighting matrix, and $\hat{\mathbf{m}}_t$ is $N \times 1$ vector of nonparametrically estimated conditional expectation of excess returns. For the CRSP Equity market portfolio ($N = 1$), the price of risk is estimated using the linear time-series regression: $R^e_{t+1} = \alpha + (\gamma_0 + \gamma_1' z_t)\widehat{Cov}_t(R^e_{t+1}, \Delta C_{t+1}/C_t) + \epsilon_{t+1}$ where $\hat{\gamma}_t = \hat{\gamma}_0 + \hat{\gamma}_1' z_t$ and z_t is a set of conditioning variables. X_t is a state variable that is standardized to a unit standard deviation – sc (Stock market wealth-to-aggregate consumption ratio), detrended sc, dfy (default yield spread, the difference between BAA and AAA-rated corporate bond yields), and yc (labor income-to-aggregate consumption ratio). NIPA Aggregate is NIPA aggregate consumption by the Bureau of Economic Analysis. CEX asset holder is the consumption of households who have a positive financial asset from the data of the Consumer Expenditure Survey by the Bureau of Labor Statistics. CRSP Equity Market is the CRSP value-weighted equity market index. Equity - FF25 portfolios is 25 size/book-to-market sorted portfolios. Equity - 100 portfolios is 25 size/book-to-market, 25 size/investment, 25 size/operating profitability, and 25 size/long-term reversal sorted portfolios. Bonds is 10 credit spread-sorted corporate bond portfolios (Nozawa, 2017) and 8 Treasury bonds. Commodities is 5 basis-sorted commodity portfolios (Yang, 2013). Currencies is 6 portfolios sorted on forward premiums (Lettau et al., 2014). ***,**,* denote the statistical significance at 1%, 5%, and 10%, respectively, based on the Hansen and Hodrick (1980) with three months lag.

	detrended sc		sc		dfy		yc	
	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat
Panel A: NIPA Aggregate								
CRSP Equity Market	-67.71	-7.40***	-45.41	-5.75***	40.65	2.40**	38.73	4.98***
Equity - FF25 portfolios	-40.58	-4.72***	-21.38	-2.44**	33.12	1.76*	13.23	1.54
Equity - 100 portfolios	-17.78	-2.05**	-1.18	-0.15	13.37	0.71	-1.67	-0.23
Bonds	2.74	0.12	21.95	1.14	11.79	0.28	-21.90	-1.07
Commodities	-30.97	-0.59	15.19	0.40	46.08	1.28	-20.82	-0.55
Currencies	-71.76	-1.54	-108.53	-2.51**	66.85	1.17	116.12	2.77***
Panel B: CEX Asset holders								
CRSP Equity Market	4.45	2.94***	4.52	3.72***	-8.95	-13.44***	-2.47	-2.18**
Equity - FF25 portfolios	4.24	2.38**	0.39	0.19	-2.93	-2.26**	-0.44	-0.21
Equity - 100 portfolios	3.90	3.97***	1.85	1.68*	-3.09	-4.23***	-1.92	-1.87*
Bonds	10.07	4.10***	2.67	1.25	-8.16	-2.68***	-2.20	-1.07
Commodities	-3.14	-0.80	-2.75	-0.84	-10.22	-3.13***	2.37	0.64
Currencies	2.72	0.53	-4.15	-0.81	2.96	0.74	3.79	0.70

Table 9. **Robustness 3: Different Specification for Ex-post Covariances**

This table presents the dynamics of the price of consumption risk, using an alternative specification for the estimation of ex-post covariances where the first principal components of 162 variables are not used in computing the residuals of consumption growth and the residuals of asset returns, for the aggregate equity portfolio and multiple asset classes using NIPA aggregate consumption and CEX asset holders' consumption based on a regression of the following equation: $\hat{\gamma}_t = a + \beta X_t + \epsilon_t$ where $\hat{\gamma}_t$ is the price of consumption risk estimated by the cross-sectional nonparametric estimation in Roussanov (2014) using N assets: $[\hat{\alpha}_t \;\; \hat{\gamma}_t]' = (\mathbf{\hat{cv}}_t' W \mathbf{\hat{cv}}_t)^{-1} \mathbf{\hat{cv}}_t' W \mathbf{\hat{m}}_t$ where $\mathbf{\hat{cv}}_t$ is $N \times 2$ vector of ones and nonparametrically estimated conditional covariances, W is the weighting matrix, and $\mathbf{\hat{m}}_t$ is $N \times 1$ vector of nonparametrically estimated conditional expectation of excess returns. For the CRSP Equity market portfolio ($N = 1$), the price of risk is estimated using the linear time-series regression: $R^e_{t+1} = \alpha + (\gamma_0 + \gamma_1' z_t)\widehat{Cov}_t(R^e_{t+1}, \Delta C_{t+1}/C_t) + \epsilon_{t+1}$ where $\hat{\gamma}_t = \hat{\gamma}_0 + \hat{\gamma}_1' z_t$ and z_t is a set of conditioning variables. X_t is a state variable that is standardized to a unit standard deviation – sc (Stock market wealth-to-aggregate consumption ratio), detrended sc, dfy (default yield spread, the difference between BAA and AAA-rated corporate bond yields), and yc (labor income-to-aggregate consumption ratio). NIPA Aggregate is NIPA aggregate consumption by the Bureau of Economic Analysis. CEX asset holder is the consumption of households who have a positive financial asset from the data of the Consumer Expenditure Survey by the Bureau of Labor Statistics. CRSP Equity Market is the CRSP value-weighted equity market index. Equity - FF25 portfolios is 25 size/book-to-market sorted portfolios. Equity - 100 portfolios is 25 size/book-to-market, 25 size/investment, 25 size/operating profitability, and 25 size/long-term reversal sorted portfolios. Bonds is 10 credit spread-sorted corporate bond portfolios (Nozawa, 2017) and 8 Treasury bonds. Commodities is 5 basis-sorted commodity portfolios (Yang, 2013). Currencies is 6 portfolios sorted on forward premiums (Lettau et al., 2014). ***,**,* denote the statistical significance at 1%, 5%, and 10%, respectively, based on the Hansen and Hodrick (1980) with three months lag.

	detrended sc		sc		dfy		yc	
	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat	$\hat{\beta}$	t-stat
Panel A: NIPA Aggregate								
CRSP Equity Market	-3.33	-2.28**	0.50	0.40	7.83	7.16***	-2.30	-1.97**
Equity - FF25 portfolios	-30.12	-3.40***	-13.66	-1.58	0.52	0.05	10.73	1.37
Equity - 100 portfolios	-2.70	-0.35	6.31	0.92	-14.07	-1.83*	-5.52	-0.81
Bonds	14.72	0.77	5.35	0.32	0.85	0.04	-0.57	-0.03
Commodities	81.30	2.86***	95.18	4.55***	-13.26	-0.70	-94.09	-4.4***
Currencies	-224.74	-4.40***	-228.25	-5.61***	131.78	1.77*	234.56	6.15***
Panel B: CEX Asset holders								
CRSP Equity Market	1.79	2.01**	-0.68	-0.87	-4.32	-6.23***	1.67	2.24**
Equity - FF25 portfolios	7.89	4.38***	2.93	1.38	-6.57	-3.75***	-2.31	-1.09
Equity - 100 portfolios	7.89	6.39***	4.73	3.19***	-6.12	-5.19***	-4.00	-2.97***
Bonds	11.25	4.37***	3.80	1.74*	-11.79	-3.53***	-1.81	-0.89
Commodities	13.58	5.11***	11.12	4.83***	-10.01	-3.84***	-12.36	-4.71***
Currencies	2.10	0.53	-4.70	-1.12	4.38	1.53	3.05	0.69

Table 10. **Robustness 4: Imposing Theoretically Consistent Sign**

This table presents the dynamics of the price of consumption risk, by imposing conditional expectation of excess returns to be zero whenever it is negative, as in Campbell and Thompson (2008), for the aggregate equity portfolio and multiple asset classes using NIPA aggregate consumption and CEX asset holders' consumption based on a regression of the following equation: $\hat{\gamma}_t = a + \beta X_t + \epsilon_t$ where $\hat{\gamma}_t$ is the price of consumption risk estimated by the cross-sectional nonparametric estimation in Roussanov (2014) using N assets: $[\hat{\alpha}_t \quad \hat{\gamma}_t]' = (\hat{\mathbf{cv}}_t' W \hat{\mathbf{cv}}_t)^{-1} \hat{\mathbf{cv}}_t' W \hat{\mathbf{m}}_t$ where $\hat{\mathbf{cv}}_t$ is $N \times 2$ vector of ones and nonparametrically estimated conditional covariances, W is the weighting matrix, and $\hat{\mathbf{m}}_t$ is $N \times 1$ vector of nonparametrically estimated conditional expectation of excess returns. X_t is a state variable that is standardized to a unit standard deviation – sc (Stock market wealth-to-aggregate consumption ratio), detrended sc, dfy (default yield spread, the difference between BAA and AAA-rated corporate bond yields), and yc (labor income-to-aggregate consumption ratio). NIPA Aggregate is NIPA aggregate consumption by the Bureau of Economic Analysis. CEX asset holder is the consumption of households who have a positive financial asset from the data of the Consumer Expenditure Survey by the Bureau of Labor Statistics. CRSP Equity Market is the CRSP value-weighted equity market index. Equity - FF25 portfolios is 25 size/book-to-market sorted portfolios. Equity - 100 portfolios is 25 size/book-to-market, 25 size/investment, 25 size/operating profitability, and 25 size/long-term reversal sorted portfolios. Bonds is 10 credit spread-sorted corporate bond portfolios (Nozawa, 2017) and 8 Treasury bonds. Commodities is 5 basis-sorted commodity portfolios (Yang, 2013). Currencies is 6 portfolios sorted on forward premiums (Lettau et al., 2014). ***,**,* denote the statistical significance at 1%, 5%, and 10%, respectively, based on the Hansen and Hodrick (1980) with three months lag.

	detrended sc		sc		dfy		yc	
	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat	$\hat{\beta}$	*t*-stat
Panel A: NIPA Aggregate								
Equity - FF25 portfolios	-34.40	-4.53***	-16.77	-2.14**	39.22	3.51***	5.06	0.69
Equity - 100 portfolios	-14.53	-2.01**	2.00	0.29	23.94	1.81*	-7.37	-1.14
Bonds	11.03	0.55	28.43	1.69*	15.85	0.43	-28.09	-1.67*
Commodities	-46.79	-1.20	-8.54	-0.30	54.00	1.58	1.84	0.06
Currencies	-49.76	-1.14	-89.17	-2.18**	54.10	1.13	100.72	2.61***
Panel B: CEX Asset holders								
Equity - FF25 portfolios	2.97	1.77*	-0.36	-0.19	-1.18	-1.03	-0.11	-0.06
Equity - 100 portfolios	2.47	2.85***	0.90	0.95	-2.00	-3.02***	-1.24	-1.37
Bonds	9.41	4.05***	2.45	1.21	-6.89	-2.49**	-2.24	-1.17
Commodities	-4.42	-1.38	-4.19	-1.56	-6.38	-2.84***	2.98	0.93
Currencies	1.31	0.32	-3.19	-0.74	7.68	1.89*	2.32	0.52

Online Appendix to: Asset holders' Consumption Risk and Tests of Conditional CCAPM

OA.1 Proof of the equation (1)

Consider a representative-agent endowment economy. The Euler equation in continuous time is

$$0 = \Lambda_t D_t dt + E_t[d(\Lambda_t S_t)], \tag{OA.17}$$

where Λ_t is the state price density and S_t is the stock price. By applying Itô's product and dividing terms by $\Lambda_t S_t$,

$$\begin{aligned} 0 &= \frac{\Lambda_t D_t}{\Lambda_t S_t}dt + E_t[\frac{S_t d\Lambda_t + \Lambda_t dS_t + dS_t d\Lambda_t}{\Lambda_t S_t}] \\ &= \frac{D_t}{S_t}dt + E_t[\frac{dS_t}{S_t}] + E_t[\frac{d\Lambda_t}{\Lambda_t}] + E_t[\frac{dS_t d\Lambda_t}{S_t \Lambda_t}] \end{aligned} \tag{OA.18}$$

Given that instantaneous total return is $dR_t = \frac{dS_t + D_t dt}{S_t}$ and the first moment of the state price density dynamics is $E_t[\frac{d\Lambda_t}{\Lambda_t}] = -r_f dt$,

$$E_t[dR_t] - r_f dt = -E_t[dR_t \frac{d\Lambda_t}{\Lambda_t}] \tag{OA.19}$$

The state price density is defined as

$$\Lambda_t = e^{-\delta_t} u'(C_t), \tag{OA.20}$$

where C_t is the consumption stream and δ is the subjective discount rate. By applying Itô's lemma, the dynamics of the state price density is

$$\frac{d\Lambda_t}{\Lambda_t} = -\delta dt + \frac{C_t u''(C_t)}{u'(C_t)}\frac{dC_t}{C_t} + \frac{1}{2}\frac{u'''(C_t)}{u'(C_t)} dC_t dC_t \tag{OA.21}$$

Plugging this equation into equation (OA.19) gives

$$E_t[dR_t] - r_f dt = -E_t[dR_t \frac{C_t u''(C_t)}{u'(C_t)}\frac{dC_t}{C_t}] = \gamma_t E_t[dR_t \frac{dC_t}{C_t}] \tag{OA.22}$$

where $\gamma_t \equiv -\frac{C_t u''(C_t)}{u'(C_t)}$. This can be re-written as

$$E_t[dR_t^e] = \gamma_t Cov_t(dR_t^e, \frac{dC_t}{C_t}) \tag{OA.23}$$

where $dR_t^e \equiv dR_t - r_f dt$

OA.2 Consumption measures from surveys

In this subsection, we describe consumption measures from CEX and NielsenIQ CPD data in detail. We use CEX and NielsenIQ data to measure asset holders' consumption as well as aggregate consumption within each data set.

OA.2.1 Consumer Expenditure Survey

The Consumer Expenditure Survey (CEX) is a nationwide household survey that is collected by the Census Bureau by the U.S. Bureau of Labor Statistics (BLS) to provide data on expenditures, income, and demographic characteristics of consumers in the United States. Surveys are collected in two surveys – the Interview Survey for major and/or recurring items and the Diary Survey, or record-keeping survey. The Diary sample interviews households for two consecutive weeks, and it is designed to obtain detailed expenditure data on small and frequently purchased items, such as food, personal care, and household supplies. CEX data are used to revise the weight of goods and services in the market basket of the Consumer Price Index. The survey has been conducted continuously since 1980. The survey consists of around 5,000 households in most waves. The CEX is the only Federal household survey to provide information on the complete range of consumers' expenditures and incomes. For this reason, this survey data set is widely used in studies of economics and finance.[20]

A selected family is interviewed about their expenditures every 3 months over five times.

[20] See Deaton and Paxson (1994),Attanasio and Jappelli (2001),Attanasio et al. (2002); Brav et al. (2002); Vissing-Jørgensen (2002a); Krueger and Perri (2006); Malloy et al. (2009); Primiceri and Van Rens (2009); Wachter and Yogo (2010); Aguiar and Hurst (2013); Aguiar and Bils (2015); Baker (2018); Parker and Souleles (2019); Cloyne et al. (2020); Cole et al. (2020); Coibion et al. (2021); Gaudio et al. (2021); Zhang (2021), for example.

Households report past 3-month expenditures on detailed categories ending in the month prior to the interview month. For example, if a household was interviewed in January 1984, the CEX reports its consumption from November to December 1983. The BLS conducts the survey on a monthly basis by introducing new households and dropping old households who finish the last interview each month. Therefore, the composition of interviewed households in a month is different from the next month, and thus, we can calculate the quarterly consumption growth at a monthly frequency. The final interview records information on earnings, income, and taxes from the preceding 12 months as well as a financial asset holding information. Following most past studies, our analyses only work with the Interview survey sample.

We follow the literature to measure consumption and filter out noisy or erroneous consumption observations. The consumption measure is nondurables plus services, and thus we exclude housing expenses (but not costs of household operations). 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. We compute the quarterly consumption growth ratio (C^h_{t+1}/C^h_t) for each household and drop extreme outliers where the consumption growth ratio is less than the bottom 1% and above 99%. Financial information is collected in the fifth interview. Therefore, we also exclude households for which any of the interviews two to five are missing. Moreover, non-urban households and households residing in student housing are excluded. We further exclude negative income, negative consumption, and zero food consumption. Our main definition of asset holders is a positive holding of "stocks, bonds, mutual funds, and other such securities", as in Vissing-Jørgensen (2002). There was a change in household identification numbers in the first quarter interview of 1986. While Malloy et al. (2009) dropped households samples that did not finish the fifth interview before the change, we match two different identification numbers by exploiting two sets[21] 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[22] in the same month, we identify them as the same households. As a result, we match the 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 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 in the same month, it turns out that they are indeed hundred percent the same households.

OA.2.2 NielsenIQ CPD data

In this subsection, we provide detailed information on the NielsenIQ CPD data, based on the description on the website, documentation, and the data.[23]

The CPD data set is provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business, available for the years from 2004 to 2019. Different from the CEX data where a household is interviewed five times, the CPD data set is a lon-

[21] CEX adds an "X" to the names of 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. This "X" file indicates that this file differs from the same quarterly file of the previous calendar year release, because it uses the methodology for the new year.

[22] 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.

[23] Please see `https://www.chicagobooth.edu/research/kilts/datasets/nielsenIQ-nielsen` for details of the data.

gitudinal panel data that keep track of the same household for a long time (approximately 9 years on average during our sample period) as long as the panel households continue to meet NielsenIQ's criteria. Moreover, while the CEX data set consists of around 5,000 households in most waves, the CPD data keep track of approximately 38,000-70,000 representative U.S. households. These households are geographically dispersed and demographically balanced.[24]

The data provide detailed demographic information of households' male/female heads that include households income range, size, type of residence, household composition, presence and age of children, age range, hours employed, education, occupation, birth year, marital status, race, and Hispanic origin. For other family members, other than family heads, birth year, employment status, and relationship/sex are collected.

For geographic information, the data provide information on households' 5-digit zip code, FIPS state, and county codes as well as region code, scantrack market code, and Designated Market Area (DM) code.

The unique feature of the CPD data set is that the data set provides detailed information on households' purchases at a daily frequency with a 12-digit Universal Product Code (UPC), which is the most granular level of product identification. They have about 1.4 million UPC codes. NielsenIQ estimates that approximately 30 percent of household consumption is accounted for by consumer panel data categories. Products include items for all retail channels – grocery, drug, mass merchandise, superstores, club stores, convenience, health, and others. All household members in the panel continually provide information to

[24]U.S. NielsenIQ samples all states (except Alaska and Hawaii) and 52 Nielsen-Defined Scantrack areas plotted in Online Appendix Figure OA.2.

NielsenIQ about products, time, and location of purchases that they make. To do so, their panel members use in-home scanners or mobile apps to record all of their purchases, from any outlet, intended for personal, in-home use. A panelist also can use an online grocery ordering service.

There are some requirements that NielsenIQ have to keep households in their sample. First, a household must be considered “active" by NielsenIQ. Second, the household must spend the minimum required amount of dollars per four-week period, depending on the household size, to be considered eligible. Past 12-month consumption of households who do not meet requirements is not reported in the data. Each year, NielsenIQ retains about 80% of its active panel.

To ensure data quality, NielsenIQ has multiple validation checks. Every quarter, they compare projected Consumer Panel data to store-based scanning data of retailers. In addition, they form a weekly sample report that tracks historical static or usable sample counts on a weekly, monthly, quarterly, and annual basis. Moreover, they assess sample representativeness of demographic characteristics and county size dispersion for each major market and the remaining U.S. sample segment on a weekly basis. They rebalance or re-weight the panel to better represent national estimates of demographic composition.

We focus on total consumption (e.g., Pukthuanthong et al., 2021) as durable types of consumption in this data account for only a small portion of the data, and the data set does not include standard durable goods such as furniture and mobile homes. To reduce noise in the data, we remove households whose total interview duration is less than 12 months. This is because households who dropped from the survey only after one year are not likely to provide precise consumption information. For consumption, we subtract the coupon value from the total price paid. For both CEX and NielsenIQ CPD data, we regress consumption growth on family size growth and monthly dummies at the household level to account for changes in consumption due to changes in family size and seasonality.

Table OA.1 reports demographic characteristics of the CEX data from 1985 to 2019 (Panel A) together with Survey of Consumer Finances from survey years of 1989, 1992, 1995, 1998, 2001, 2004, 2007, 2010, 2013, 2016, and 2019 (Panel B) and NielsenIQ data from 2004 to 2019 (Panel C). Panel A shows that from the CEX data, asset holders are more likely to be better educated (less high school degrees but more college degrees), older, higher income, more white, male, and married than non-asset holders. The same patterns are observed in the SCF data, where asset holders are accurately measured, although the data span a different time period. This supports the validity of the CEX data. In NielsenIQ data, we do not directly observe the identification of asset holders. Instead, we use the consumption of households who live in a county which is in the top 10% highest dividend income to aggregate income ratio. Panel C shows that, consistent with the CEX and SCF data sets, assumed asset holders in NielsenIQ data are better educated, older, and higher income than non-asset holders. However, households in the top 10% county are not more white, male, and married, different from CEX and SCF data set.

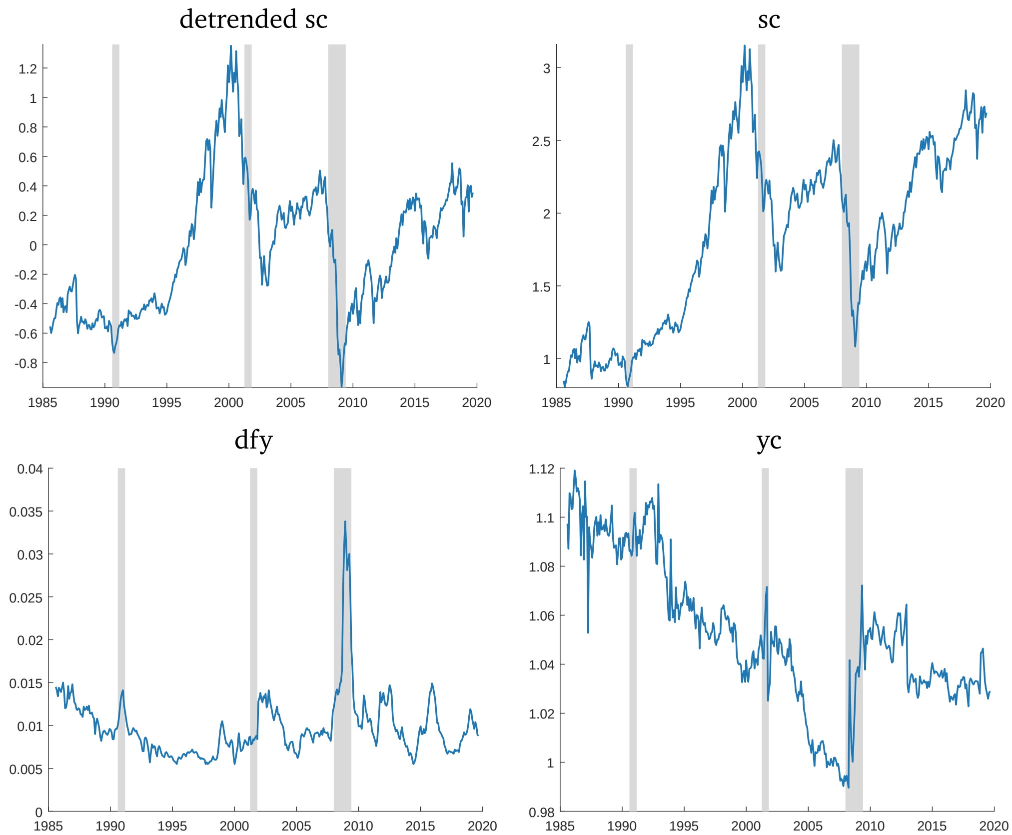

Figure OA.1. **State variables**

This figure plots state variables: sc (Stock market wealth-to-aggregate consumption ratio), detrended sc, dfy (default yield spread, the difference between BAA and AAA-rated corporate bond yields), and yc (labor income-to-aggregate consumption ratio). Shaded areas denote the NBER recessions.

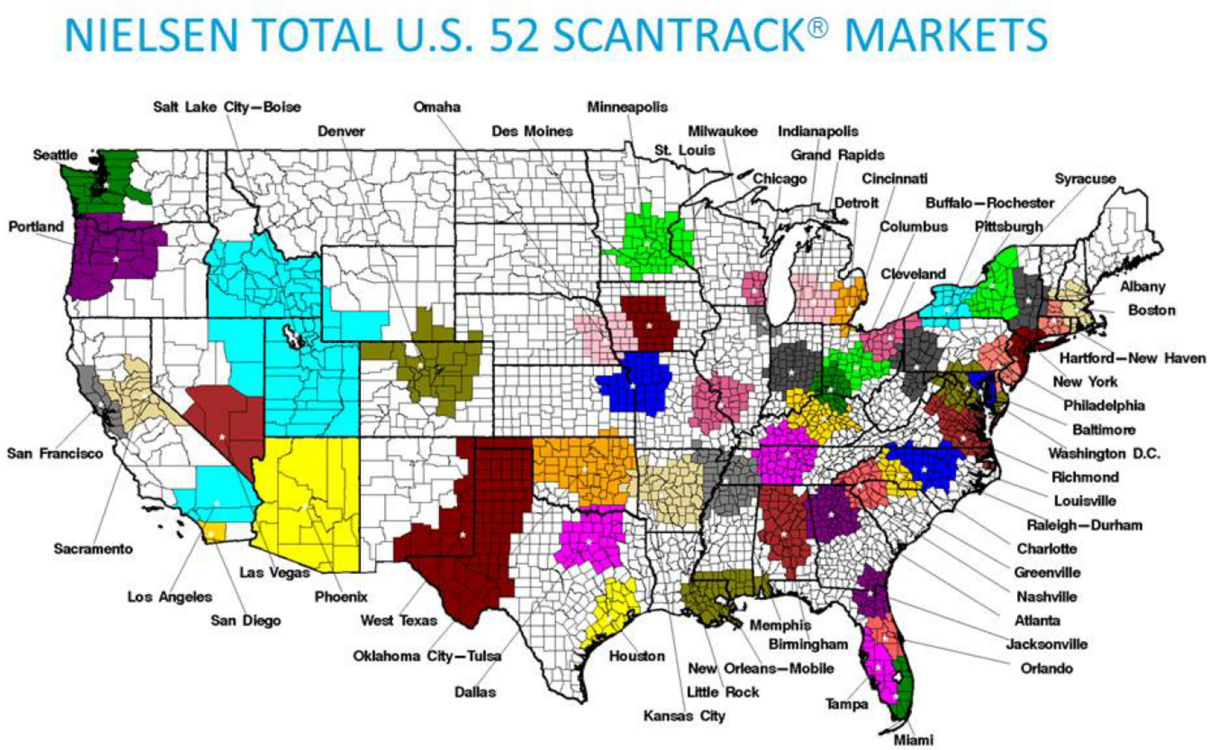

Figure OA.2. 52 Nielsen Scantrack markets

This figure presents 52 Nielsen Scantrack markets that Nielsen panelists are located in.

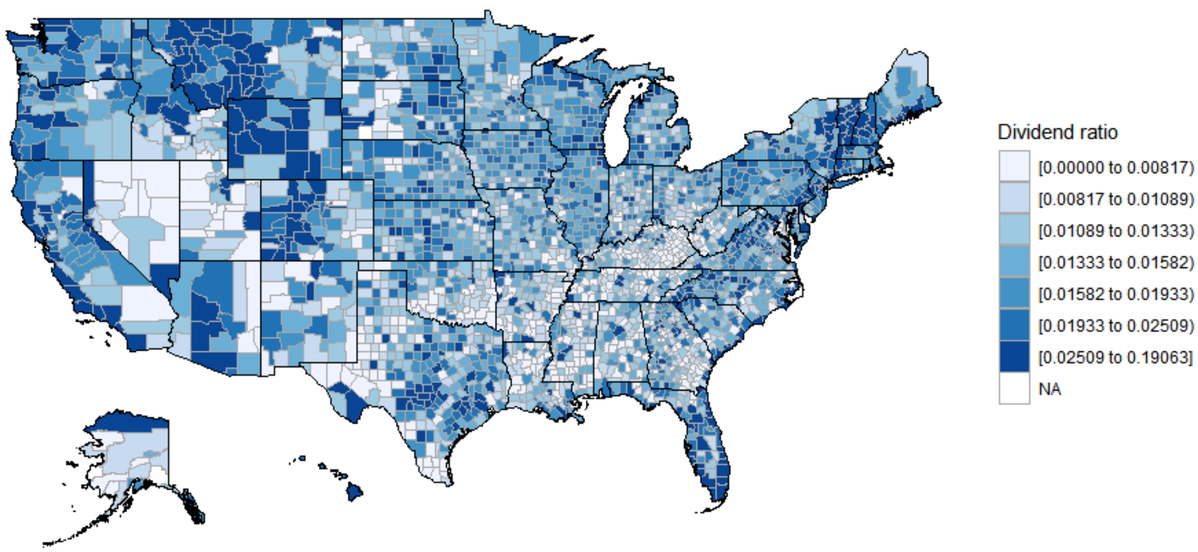

Figure OA.3. Stock market participation using IRS data

This figure shows the ratio of aggregate dividend income over aggregate taxable income for U.S. counties in 2019 using the data of IRS Statistics of Income.

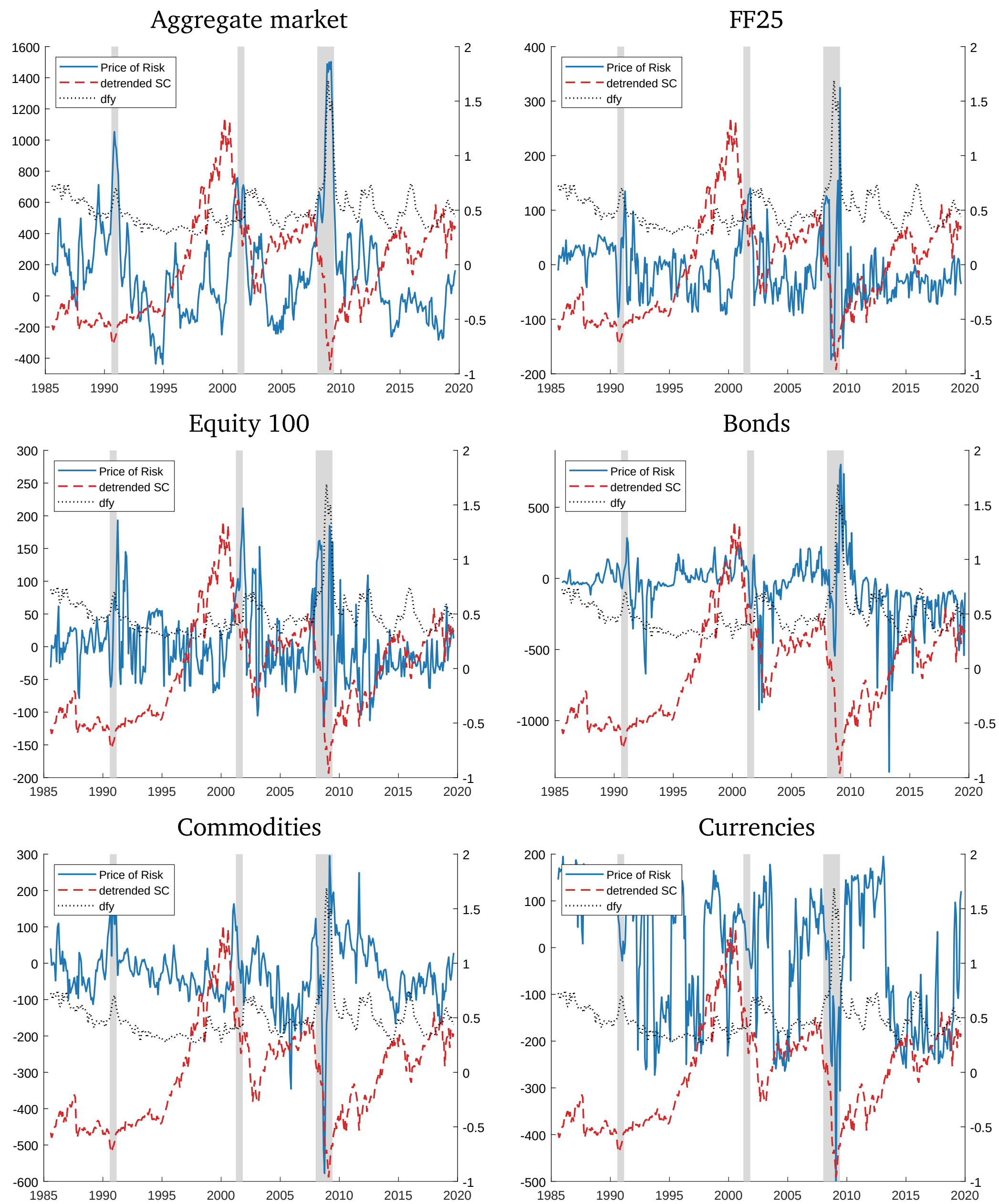

Figure OA.4. **Conditional Price of Consumption risk for Each Portfolio Group using CEX Aggregate consumption**

This figure plots the conditional price of consumption risk estimated using each portfolio group and the cross-sectional nonparametric estimation by Roussanov (2014): $\hat{\gamma}_t = (\hat{\mathbf{cv}}_t' W \hat{\mathbf{cv}}_t)^{-1} \hat{\mathbf{cv}}_t' W \hat{\mathbf{m}}_t$ where $\hat{\mathbf{cv}}_t$ is $N \times 2$ vector of ones and nonparametrically estimated conditional covariances, W is the weighting matrix, and $\hat{\mathbf{m}}_t$ is $N \times 1$ vector of nonparametrically estimated conditional expectation of excess returns. The blue-solid line is the price of consumption risk. The red-dashed line is the detrended stock market wealth-to-aggregate consumption ratio. The black-dotted line is the default yield spread (dfy), the difference between BAA and AAA-rated corporate bond yields. Shaded areas denote the NBER recessions.

Table OA.1. **Demographic Characteristics of Asset holders**

This table presents demographic characteristics of asset holders versus non-asset holders in the CEX and SCF (Survey of Consumer Finances) data. Reported are average values of demographic variables.

	High	College	Age	Income	Nonwhite	Male	Married
			Panel A: CEX data				
Non-holders	0.25	0.47	44.46	26,426	0.19	0.54	0.59
Asset holders	0.10	0.54	46.32	46,903	0.08	0.67	0.71
Total	0.22	0.48	44.73	29,328	0.18	0.56	0.61
t-stat	-99.22	30.85	35.40	115.287	-81.71	54.53	52.43
			Panel B: SCF data				
Non-holders	0.50	0.39	49.71	41,324	0.36	0.64	0.47
Asset holders	0.28	0.70	50.05	128,668	0.18	0.80	0.69
Total	0.39	0.55	49.88	84,807	0.27	0.72	0.58
t-stat	-42.68	62.42	1.82	77.13	-41.55	34.39	42.17
			Panel C: Nielsen IQ data				
Non-holders	0.31	0.68	50.38	25,716	0.22	0.71	0.51
Asset holders	0.25	0.74	51.14	27,277	0.26	0.69	0.48
Total	0.30	0.70	50.54	26,047	0.23	0.71	0.51
t-stat	-105.17	104.99	46.93	70.00	68.78	-39.24	-58.65

Table OA.2. **State Variables**

Table presents the list of conditioning 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) $\Delta(z_t/z_{t-1} - 1)$.

Number	Name	Description	Group	tcode
1	RPI	Real Personal Income	Group 1: Output and Income	5
2	W875RX1	Real personal income ex transfer receipts	Group 1: Output and Income	5
3	INDPRO	IP Index	Group 1: Output and Income	5
4	IPFPNSS	IP: Final Products and Nonindustrial Supplies	Group 1: Output and Income	5
5	IPFINAL	IP: Final Products (Market Group)	Group 1: Output and Income	5
6	IPCONGD	IP: Consumer Goods	Group 1: Output and Income	5
7	IPDCONGD	IP: Durable Consumer Goods	Group 1: Output and Income	5
8	IPNCONGD	IP: Nondurable Consumer Goods	Group 1: Output and Income	5
9	IPBUSEQ	IP: Business Equipment	Group 1: Output and Income	5
10	IPMAT	IP: Materials	Group 1: Output and Income	5
11	IPDMAT	IP: Durable Materials	Group 1: Output and Income	5
12	IPNMAT	IP: Nondurable Materials	Group 1: Output and Income	5
13	IPMANSICS	IP: Manufacturing (SIC)	Group 1: Output and Income	5
14	IPB51222S	IP: Residential Utilities	Group 1: Output and Income	5
15	IPFUELS	IP: Fuels	Group 1: Output and Income	5
16	CUMFNS	Capacity Utilization: Manufacturing	Group 1: Output and Income	2
17	COS	Consumer Opinion Surveys: Confidence Indicators	Group 1: Output and Income	4
18	RECPROUSM156N	Smoothed U.S. Recession Probabilities	Group 1: Output and Income	1
19	SAHMCURRENT	Sahm Rule Recession Indicator	Group 1: Output and Income	1
20	HWI	Help-Wanted Index for United States	Group 2: Labor Market	2
21	HWIURATIO	Ratio of Help Wanted/No. Unemployed	Group 2: Labor Market	2
22	CLF16OV	Civilian Labor Force	Group 2: Labor Market	5
23	CE16OV	Civilian Employment	Group 2: Labor Market	5
24	UNRATE	Civilian Unemployment Rate	Group 2: Labor Market	2
25	UEMPMEAN	Average Duration of Unemployment (Weeks)	Group 2: Labor Market	2
26	UEMPLT5	Civilians Unemployed - Less Than 5 Weeks	Group 2: Labor Market	5
27	UEMP5TO14	Civilians Unemployed for 5-14 Weeks	Group 2: Labor Market	5
28	UEMP15OV	Civilians Unemployed - 15 Weeks & Over	Group 2: Labor Market	5
29	UEMP15T26	Civilians Unemployed for 15-26 Weeks	Group 2: Labor Market	5
30	UEMP27OV	Civilians Unemployed for 27 Weeks and Over	Group 2: Labor Market	5
31	CLAIMSx	Initial Claims	Group 2: Labor Market	5
32	PAYEMS	All Employees: Total nonfarm	Group 2: Labor Market	5
33	USGOOD	All Employees: Goods-Producing Industries	Group 2: Labor Market	5
34	CES1021000001	All Employees: Mining and Logging: Mining	Group 2: Labor Market	5
35	USCONS	All Employees: Construction	Group 2: Labor Market	5
36	MANEMP	All Employees: Manufacturing	Group 2: Labor Market	5
37	DMANEMP	All Employees: Durable goods	Group 2: Labor Market	5
38	NDMANEMP	All Employees: Nondurable goods	Group 2: Labor Market	5
39	SRVPRD	All Employees: Service-Providing Industries	Group 2: Labor Market	5
40	USTPU	All Employees: Trade, Transportation & Utilities	Group 2: Labor Market	5
41	USWTRADE	All Employees: Wholesale Trade	Group 2: Labor Market	5
42	USTRADE	All Employees: Retail Trade	Group 2: Labor Market	5
43	USFIRE	All Employees: Financial Activities	Group 2: Labor Market	5
44	USGOVT	All Employees: Government	Group 2: Labor Market	5
45	CES0600000007	Avg Weekly Hours : Goods-Producing	Group 2: Labor Market	1
46	AWOTMAN	Avg Weekly Overtime Hours : Manufacturing	Group 2: Labor Market	2
47	AWHMAN	Avg Weekly Hours : Manufacturing	Group 2: Labor Market	1
48	CES0600000008	Avg Hourly Earnings : Goods-Producing	Group 2: Labor Market	6
49	CES2000000008	Avg Hourly Earnings : Construction	Group 2: Labor Market	6
50	CES3000000008	Avg Hourly Earnings : Manufacturing	Group 2: Labor Market	6
51	HOUST	Housing Starts: Total New Privately Owned	Group 3: Consumption and Orders	4
52	HOUSTNE	Housing Starts, Northeast	Group 3: Consumption and Orders	4
53	HOUSTMW	Housing Starts, Midwest	Group 3: Consumption and Orders	4
54	HOUSTS	Housing Starts, South	Group 3: Consumption and Orders	4
55	HOUSTW	Housing Starts, West	Group 3: Consumption and Orders	4

Table OA.2 – continued from previous page

Number	Name	Description	Group	tcode
56	PERMIT	New Private Housing Permits (SAAR)	Group 3: Consumption and Orders	4
57	PERMITNE	New Private Housing Permits, Northeast (SAAR)	Group 3: Consumption and Orders	4
58	PERMITMW	New Private Housing Permits, Midwest (SAAR)	Group 3: Consumption and Orders	4
59	PERMITS	New Private Housing Permits, South (SAAR)	Group 3: Consumption and Orders	4
60	PERMITW	New Private Housing Permits, West (SAAR)	Group 3: Consumption and Orders	4
61	ACOGNO	New Orders for Consumer Goods	Group 4: Orders and Inventories	5
62	AMDMNOx	New Orders for Durable Goods	Group 4: Orders and Inventories	5
63	ANDENOx	New Orders for Nondefense Capital Goods	Group 4: Orders and Inventories	5
64	AMDMUOx	Unfilled Orders for Durable Goods	Group 4: Orders and Inventories	5
65	BUSINVx	Total Business Inventories	Group 4: Orders and Inventories	5
66	ISRATIOx	Total Business: Inventories to Sales Ratio	Group 4: Orders and Inventories	2
67	DPCERA3M086SBEA	Real personal consumption expenditures	Group 4: Orders and Inventories	5
68	CMRMTSPLx	Real Manu. and Trade Industries Sales	Group 4: Orders and Inventories	5
69	RETAILx	Retail and Food Services Sales	Group 4: Orders and Inventories	5
70	UMCSENTx	Consumer Sentiment Index	Group 4: Orders and Inventories	2
71	M1SL	M1 Money Stock	Group 5: Money and Credit	6
72	M2SL	M2 Money Stock	Group 5: Money and Credit	6
73	M2REAL	Real M2 Money Stock	Group 5: Money and Credit	5
74	BOGMBASE	Monetary Base; Total	Group 5: Money and Credit	6
75	TOTRESNS	Total Reserves of Depository Institutions	Group 5: Money and Credit	6
76	NONBORRES	Reserves Of Depository Institutions	Group 5: Money and Credit	7
77	BUSLOANS	Commercial and Industrial Loans	Group 5: Money and Credit	6
78	REALLN	Real Estate Loans at All Commercial Banks	Group 5: Money and Credit	6
79	NONREVSL	Total Nonrevolving Credit	Group 5: Money and Credit	6
80	CONSPI	Nonrevolving consumer credit to Personal Income	Group 5: Money and Credit	2
81	MZMSL	MZM Money Stock	Group 5: Money and Credit	6
82	DTCOLNVHFNM	Consumer Motor Vehicle Loans Outstanding	Group 5: Money and Credit	6
83	DTCTHFNM	Total Consumer Loans and Leases Outstanding	Group 5: Money and Credit	6
84	INVEST	Securities in Bank Credit at All Commercial Banks	Group 5: Money and Credit	6
85	WPSFD49207	PPI by Commodity:Final Demand: Finished Goods	Group 6: Prices	6
86	WPSFD49502	PPI by Commodity: Final Demand: Personal Consumption Goods	Group 6: Prices	6
87	WPSID61	PPI by Commodity: Intermediate Demand, Processed Goods	Group 6: Prices	6
88	WPSID62	PPI by Commodity: Intermediate Demand, Unprocessed Goods	Group 6: Prices	6
89	OILPRICEx	Crude Oil, spliced WTI and Cushing	Group 6: Prices	6
90	PPICMM	PPI: Metals and metal products	Group 6: Prices	6
91	CPIAUCSL	CPI : All Items	Group 6: Prices	6
92	CPIAPPSL	CPI : Apparel	Group 6: Prices	6
93	CPITRNSL	CPI : Transportation	Group 6: Prices	6
94	CPIMEDSL	CPI : Medical Care	Group 6: Prices	6
95	CUSR0000SAC	CPI : Commodities	Group 6: Prices	6
96	CUSR0000SAD	CPI : Durables	Group 6: Prices	6
97	CUSR0000SAS	CPI : Services	Group 6: Prices	6
98	CPIULFSL	CPI : All Items Less Food	Group 6: Prices	6
99	CUSR0000SA0L2	CPI : All items less shelter	Group 6: Prices	6
100	CUSR0000SA0L5	CPI : All items less medical care	Group 6: Prices	6
101	PCEPI	Personal Cons. Expend.: Chain Index	Group 6: Prices	6
102	DDURRG3M086SBEA	Personal Cons. Exp: Durable goods	Group 6: Prices	6
103	DNDGRG3M086SBEA	Personal Cons. Exp: Nondurable goods	Group 6: Prices	6
104	DSERRG3M086SBEA	Personal Cons. Exp: Services	Group 6: Prices	6
105	FEDFUNDS	Effective Federal Funds Rate	Group 7: Interest rate and Exchange Rates	2
106	CP3Mx	3-Month AA Financial Commercial Paper Rate	Group 7: Interest rate and Exchange Rates	2
107	TB3MS	3-Month Treasury Bill	Group 7: Interest rate and Exchange Rates	2
108	TB6MS	6-Month Treasury Bill	Group 7: Interest rate and Exchange Rates	2
109	GS1	1-Year Treasury Rate	Group 7: Interest rate and Exchange Rates	2
110	GS5	5-Year Treasury Rate	Group 7: Interest rate and Exchange Rates	2

Table OA.2 – continued from previous page

Number	Name	Description	Group	tcode
111	GS10	10-Year Treasury Rate	Group 7: Interest rate and Exchange Rates	2
112	AAA	Moody's Seasoned Aaa Corporate Bond Yield	Group 7: Interest rate and Exchange Rates	2
113	BAA	Moody's Seasoned Baa Corporate Bond Yield	Group 7: Interest rate and Exchange Rates	2
114	COMPAPFFx	3-Month Commercial Paper Minus FEDFUNDS	Group 7: Interest rate and Exchange Rates	1
115	TB3SMFFM	3-Month Treasury C Minus FEDFUNDS	Group 7: Interest rate and Exchange Rates	1
116	TB6SMFFM	6-Month Treasury C Minus FEDFUNDS	Group 7: Interest rate and Exchange Rates	1
117	T1YFFM	1-Year Treasury C Minus FEDFUNDS	Group 7: Interest rate and Exchange Rates	1
118	T5YFFM	5-Year Treasury C Minus FEDFUNDS	Group 7: Interest rate and Exchange Rates	1
119	T10YFFM	10-Year Treasury C Minus FEDFUNDS	Group 7: Interest rate and Exchange Rates	1
120	AAAFFM	Moody's Aaa Corporate Bond Minus FEDFUNDS	Group 7: Interest rate and Exchange Rates	1
121	BAAFFM	Moody's Baa Corporate Bond Minus FEDFUNDS	Group 7: Interest rate and Exchange Rates	1
122	TWEXAFEGSMTHx	Trade Weighted U.S. Dollar Index: Major Currencies	Group 7: Interest rate and Exchange Rates	5
123	EXSZUSx	Switzerland / U.S. Foreign Exchange Rate	Group 7: Interest rate and Exchange Rates	5
124	EXJPUSx	Japan / U.S. Foreign Exchange Rate	Group 7: Interest rate and Exchange Rates	5
125	EXUSUKx	U.S. / U.K. Foreign Exchange Rate	Group 7: Interest rate and Exchange Rates	5
126	EXCAUSx	Canada / U.S. Foreign Exchange Rate	Group 7: Interest rate and Exchange Rates	5
127	LTY	Long-term yield	Group 7: Interest rate and Exchange Rates	2
128	TMS	Term spread	Group 7: Interest rate and Exchange Rates	1
129	DFY	Default yield	Group 7: Interest rate and Exchange Rates	1
130	DFR	Default returns	Group 7: Interest rate and Exchange Rates	1
131	RREL	Relative T-bill rate	Group 7: Interest rate and Exchange Rates	1
132	S&P 500	S&P 500's Common Stock Price Index: Composite	Group 8: Stock Market	5
133	S&P: indust	S&P 500's Common Stock Price Index: Industrials	Group 8: Stock Market	5
134	S&P div yield	S&P 500's Composite Common Stock: Dividend Yield	Group 8: Stock Market	2
135	S&P PE ratio	S&P 500's Composite Common Stock: Price-Earnings Ratio	Group 8: Stock Market	5
136	VIXCLSx	S&P 500 implied volatility	Group 8: Stock Market	1
137	DE	Dividend Payout Ratio	Group 8: Stock Market	1
138	SVAR	S&P 500 Realized variance	Group 8: Stock Market	1
139	BM	Book-to-Market Ratio	Group 8: Stock Market	1
140	NTIS	Net Equity Expansion	Group 8: Stock Market	1
141	RA-BEX	Risk aversion in Bekaert et al. (2022)	Group 8: Stock Market	1
142	EPU	Economic Policy Uncertainty in Baker et al. (2016)	Group 9: Uncertainty	1
143	EPU-FISCAL	Fiscal Policy (Taxes OR Spending) EPU in Baker et al. (2016)	Group 9: Uncertainty	1
144	EPU-TAX	Taxes EPU in Baker et al. (2016)	Group 9: Uncertainty	1
145	EPU-GOV	Government spending EPU in Baker et al. (2016)	Group 9: Uncertainty	1
146	EPU-HEALTH	Health care EPU in Baker et al. (2016)	Group 9: Uncertainty	1
147	EPU-NATIONAL	National security EPU in Baker et al. (2016)	Group 9: Uncertainty	1
148	EPU-ENTITLEMENT	Entitlement programs EPU in Baker et al. (2016)	Group 9: Uncertainty	1
149	EPU-REGULATION	Regulation EPU in Baker et al. (2016)	Group 9: Uncertainty	1
150	EPU-FINANCIAL	Financial Regulation EPU in Baker et al. (2016)	Group 9: Uncertainty	1
151	EPU-TRADE	Trade policy EPU in Baker et al. (2016)	Group 9: Uncertainty	1
152	EPU-SOVEREIGN	Sovereign debt, currency crises EPU in Baker et al. (2016)	Group 9: Uncertainty	1
153	MAC-UN	Macro Economic Uncertainty in Jurado et al. (2015)	Group 9: Uncertainty	1
154	MPU-WORLD	Monetary EPU in Baker et al. (2016)	Group 9: Uncertainty	1
155	MPU-HRS	Monetary Policy Uncertainty in Husted et al. (2020)	Group 9: Uncertainty	1
156	CPU	Climate Policy Uncertainty Index in Gavriilidis (2021)	Group 9: Uncertainty	1
157	GPR	Geopolitical Risk index in Caldara and Iacoviello (2022)	Group 9: Uncertainty	1

Table OA.2 – continued from previous page

Number	Name	Description	Group	tcode
158	EMV	Daily Infectious Disease Equity Market Volatility in Baker et al. (2020)	Group 9: Uncertainty	8
159	GEPU	Global EPU in Baker et al. (2016)	Group 9: Uncertainty	2
160	CAY	consumption-wealth ratio in Lettau and Ludvigson (2001)	Group 10: Other state variable	1
161	YC	income-consumption ratio in Santos and Veronesi (2006)	Group 10: Other state variable	1
162	CA	consumption-wealth ratio in Roussanov (2014)	Group 10: Other state variable	1

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