Asset Pricing with Daily Shopper Spending *

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Abstract:

We propose a novel consumption measure that has a daily frequency and is derived from real-time shopping data. Our measure solves the joint equity premium and risk-free rate puzzles with a risk aversion coefficient much lower than any other consumption measure. It can explain the cross-sectional variation in expected returns on various portfolios and individual stocks. By decomposing consumption shocks into different frequencies of volatility, our model demonstrates that the lack of short-term dynamics and intra-annual fluctuations in low-frequency consumption measures results in significantly higher levels of risk aversion.

JEL C12, E21, E44, G12

Key Words: Consumption-based Asset Pricing, Consumption Dynamics, Equity Premium.

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Can consumption risk adequately explain the equity premium? The past dozen years have witnessed an explosion of studies striving to answer this critical question. Early empirical evidence offers little support for the consumption-based capital asset pricing model (CCAPM) of Lucas (1978) and Breeden (1979). This failure of the CCAPM has led to an explosive development of the characteristics-based asset pricing model. It has spurred the development of adaptive versions of consumption-based asset pricing models that allow for a more general representation of investors' preferences or impose new restrictions on the dynamics of cash flow fundamentals or new market structures.[1] However, the limited success of this classic model can be attributed to the measured consumption, which has a low frequency and suffers from measurement error.

This paper introduces a new measure of consumption that aligns with the CCAPM theory and, thus, mitigates the reliance on such models. Our innovative consumption measure captures households' daily spending on all trips related to food and groceries, providing a real-time synchronization with asset returns. Our consumption measure offers a more precise assessment of actual expenditures and a time stamp that has been unavailable in other consumption measures until now. In particular, traditional measures represent consumption flows over discrete intervals, leading to time aggregation bias and measurement error, both of which arise from the complex procedures used in their construction.[2]

In contrast, our data are pristine and free of complex procedures that cause time aggregation bias or measurement error. By capturing households' daily spending on food and groceries, our measure precisely reflects consumption patterns to enable us to evaluate the role of consumption risk in explaining the equity premium.

We do not assert the superiority of our daily measure over other consumption measures, as

[1]The characteristics-based asset pricing model falls victim to the "factor zoo" debate, which refers to the high rate of factor production in the literature. Researchers have proposed over 100 characteristics and 400 factors, but many suggest that some are false or simply lucky findings. For adaptive versions of CCAPM, see Epstein and Zin (1989), Sundaresan (1989), Constantinides (1990), Abel (1990), Heaton (1995), and Campbell and Cochrane (1999) (more general preferences for consumption at different points in time). See also Restoy and Weil (2011), Bansal and Yaron (2004), and Bansal et al. (2012) for long-run risks; Constantinides and Duffie (1996) for market incompleteness; and Mankiw and Zeldes (1991) for limited market participation.

[2]Time aggregation bias refers to the distortion in data that arises when data are aggregated over periods that are too large relative to the underlying variability of the data. Measurement errors include benchmarking, non-reporting bias, and the residual method. Savov (2011) uses garbage to capture actual consumption, but his measure is not completely error-free, as described in his Internet Appendix. Kroencke (2017) unfilters the national income and product accounts (NIPA) data to reduce measurement errors and attempts to avoid time aggregation bias by adding a correction factor to the unfiltered recursion.

direct comparisons are not feasible.[3] Rather, our objective is to propose a high-frequency measure of consumption growth that can adequately explain the equity premium paradox, effectively price asset returns cross-sectionally, and pass the rank test of Kleibergen and Zhan (2020), henceforth KZ, applied to a range of testing assets.

For spending to accurately reflect consumption, the products purchased must be consumed on the same day. Our data represent a reasonable approximation of consumption. It primarily consists of nondurable goods, with relatively slow-to-consume goods composing less than 10%, and none being typical durable goods (see Table 1 for the breakdown). Furthermore, to ensure that the spending data accurately represent consumption, we conduct additional analyses using products that require immediate consumption, such as deli sandwiches or in-store baked pizzas. Our results remain robust, further supporting the validity of our consumption measure.

Despite the theoretical foundation for the relationship between daily stock returns and household consumption, the evidence on the topic is limited, primarily because of the absence of daily consumption statistics.[4] In this study, we utilize Consumer Panel Data (CPD) to develop a real-time measure of daily consumption and test this theoretical framework empirically. Our analysis involves regressing households' daily consumption on Fama-French risk factors, and the results reveal a positive correlation between daily consumption and systematic risks. Additionally, we construct a weekly measure, with the findings allowing us to make qualitative comparisons with the daily measure.

Notably, our cross-sectional asset pricing test is conducted daily, aligning with daily consumption growth. A daily application provides certain advantages, as a daily return prediction is more challenging than a monthly one. Extant literature demonstrates that stock predictability is more likely to occur over longer horizons.[5] Cochrane (2009) posits that expected asset returns depend on risk aversion, risk (consumption volatility), and the correlation between asset returns and the stochastic discount factor. According to Cochrane (2009), these factors are more likely to change

[3]Most consumption growth measures rely on the National Income and Product Accounts (NIPA). Although NIPA provides quarterly and monthly survey data, inaccuracies arise with higher-frequency NIPA data because consumption estimates are derived from a selected sample rather than the entire population. Consequently, most consumption-based studies employ annual data from NIPA. To enable a direct comparison between our daily measures and these annual measures, we must aggregate them to an annual frequency. However, this aggregation process results in substantial information loss, as elaborated on in Section 2.1. Thus, comparing aggregated consumption measures with other annual measures would distort our daily measures.

[4]See Guiso and Haliassos (2001) for the theoretical relationship between stock returns and consumption.

over long-term than short-term horizons, such as daily. That is to say, asset returns are more likely to be predictable over longer horizons. Given the challenges of predicting daily asset returns, developing an asset pricing test that accounts for daily frequency is essential. Furthermore, compared with a monthly frequency, the daily frequency allows us to estimate beta more reliably, which is prone to an error-in-variable bias.

We further provide a theoretical explanation of the superior performance of daily consumption measures by breaking down consumption volatility (high-frequency volatility) into short-run dynamics and low-frequency volatility. We show that, ceteris paribus, neglecting either component, could decrease consumption volatility and stock market covariances and raise estimates of relative risk aversion. Specifically, we present a coherent framework by fitting the autoregressive spline generalized autoregressive conditional heteroscedasticity (AR-spline-GARCH) model to our data. Two components characterize our measure: (1) time-series dynamics (short-term fluctuations), which are ignored in the annual consumption measure, and (2) the slowly evolving macroeconomic effect (low-frequency volatility), which comprises intra-annual fluctuations and long-term trends.

Compared to intra-annual fluctuations and short-term dynamics, long-term trends characterize the annual consumption measure. Low-frequency consumption loses most of its information during aggregation and, as a result, has less variation than stock returns. We show that the long-term trend alone is smooth and leads to huge risk aversion. Noise shock is an essential source of short-term fluctuations. Households continuously receive future-related information, such as news or noise. Based on this information, households decide on consumption and investments. If ex posts the information pertains to fundamentals, the economy gradually adjusts to that information representing low-frequency volatility. If it is noise, the economy returns to its initial state, captured by short-term dynamics. Since news and noise have pricing implications for stock returns, a good state variable must capture both. Our daily consumption measure has high variability and contains both components.[6] Liu and Matthies (2022) show evidence supporting our premise: they find that about 80% of the pricing power of five alternative consumption measures comes from the short-horizon component.

[5]See Fama and French (1988), Campbell and Thompson (2008), and Cochrane (2008).

[6]See Brogaard et al. (2022) and Ang et al. (2021) for the role of news and noise in stock price movements.

Compared to measures using garbage or unfiltered NIPA, our measure can account for the observed equity premium with a relative risk aversion (RRA) coefficient of 9.217. It generates a considerably low risk-free rate between 0.003% and −0.091%. Also, in a joint pricing test, the daily consumption-based model fittingly explains the equity premium and risk-free rate with a mean absolute error (MAE) of 0.467% and a low-risk aversion of 5.159. These results align with the argument for using an improved consumption measure in asset valuation. When using a daily consumption measure, the CCAPM matches the equity premium with a low relative risk aversion and implies a risk-free rate consistent with the actual interest rate. Therefore, we provide a formal solution to the puzzle concerning the simultaneous equity premium and the risk-free rate. Our results remain robust even when applied out-of-sample from 2016 to 2018.

Since our measure is daily, while garbage and unfiltered NIPA are annual, some may argue the superior performance is driven by frequency. Although direct annual comparisons are not feasible for the reasons already discussed (see footnote 3), we can approximate a fair comparison. To do this, we adopt a factor-mimicking portfolio approach to construct a tradable version of the daily consumption series extending back to 1960, when data for other measures are available. We aggregate this time series to an annual frequency and demonstrate that our measure outperforms the other measures. Our relative risk aversion (RRA) estimate is the lowest (7.477) compared to that of garbage (15.63), unfiltered NIPA (22.53), PJ (42.35), and Q4-Q4 (64.05). Additionally, our implied risk-free rate is the lowest among all other measures, except for garbage, which generates an implied risk-free rate that is 1.08% lower than ours.

In the second part of our study, we evaluate the ability of the daily consumption-based model to explain stock returns cross-sectionally. To this end, we utilize Jegadeesh et al. (2019)'s instrumental variable approach to reduce the error-in-variable bias during beta estimation. This approach allows us to assess individual stocks more comprehensively, providing richer information than portfolios.[7] Lewellen et al. (2010) highlight how the choice of testing assets can affect the statistical significance of risk premiums. To ensure the robustness of our findings, we subject our results to a battery of tests involving a large and diverse set of assets, such as 25 size and book-to-market portfolios by Fama and French (1996), Feng et al. (2020) testing assets and individual stocks. Because of the limited frequency of their data, extant measures of consumption may not allow for a wide range of testing assets. Our results corroborate the Cochrane (2009) assertion that consumption-based asset pricing models should outperform other asset pricing models in explaining stock returns cross-sectionally. Specifically, we observe a positive and significant premium associated with daily consumption growth, with a low mean absolute percentage error (MAPE). Importantly, our results are robust across the various testing assets employed.

The granularity of our data works in our favor to help us uncover new economic insights. Specifically, we investigate whether spending growth on products requiring instantaneous consumption explains stock returns variation better than products that demand relatively slow consumption. Our results reveal that the estimated coefficient for relative risk aversion declines from 9.217 for regular products to 7.96 for products requiring instantaneous consumption. Conversely, for slow-consumption products, such as nonfood grocery and general merchandise, the risk aversion coefficient is 9.698. This outcome supports the Campbell (2018) argument that the consumption-based capital asset pricing model should apply particularly well to instantaneous consumption.

The high-frequency nature of our data further enables us to examine the potential application of our findings to hedging consumption risk. In a vein similar to that of Engle et al. (2020)'s hedging climate change portfolio, we identify an investment strategy that involves long positions in industrial and commercial machinery and computer equipment and short positions in foods and kindred products. Our results demonstrate that this strategy can effectively hedge consumption risk while generating high excess returns. The demand for industrial and commercial machinery and computer equipment may increase with rising consumer wealth and decreasing consumer risk.

Next, we undertake three specific robustness tests. First, we create a consumption-mimicking portfolio (CMP) using daily frequency data within the same sample period and find that results with the CMP remain strong. Other researchers who wish to validate our results can use this portfolio as a replication tool.[8] Second, to address the potential seasonality issue in our consumption growth data, we decompose our data into a trend, seasonality, and idiosyncratic components. Upon removing trends and seasonality, we observe similar qualitative results. Third, our analysis reveals that the households that spend the most on consumption have the lowest risk aversion,

[7] Jegadeesh et al. (2019) advocate using individual assets as test assets instead of portfolios, as the latter can obscure essential risk- or return-related features. To address this issue, they propose an instrumental variable approach that employs individual assets, thus allowing them to capture more detailed information about the assets' characteristics.

consistent with the argument by Ait-Sahalia et al. (2004).

Our paper builds on a growing literature that proposes alternative measures of consumption risk to improve the performance of consumption-based asset pricing models. Ait-Sahalia et al. (2004) find that luxury goods have a more remarkable pricing ability than aggregate consumption. Jagannathan and Wang (2007) show that the CCAPM performs well with fourth-quarter NIPA consumption. Savov (2011) finds that garbage growth, as a proxy for consumption growth, prices portfolio returns cross-sectionally. Chen et al. (2020) and Da et al. (2016) report similar results using carbon dioxide emissions and electricity consumption as proxies for consumption. Using household data, Yogo (2006) studies the pricing role of durable consumption. Malloy et al. (2009) use stockholder consumption to price size and value portfolios. Qiao (2013) and Kroencke (2017) address the shortcomings of NIPA consumption using filtered and unfiltered consumption, respectively. Liu and Matthies (2022) introduce an innovative consumption growth measure derived from news.

This paper also relates to the extensive literature studying the underlying stochastic consumption growth process. Keloharju et al. (2012) show that investors tend to buy the stocks of companies in which they shop, thereby discovering a positive relation between shopping and stock ownership. Bansal et al. (2014) and Campbell (2018) argue that volatility shocks are priced, even conditional on shocks to the mean. Tédongap (2015) estimates the conditional volatility of consumption through a GARCH model and shows that its innovations lead to a risk premium in the value stocks. Bandi and Tamoni (2017) and Boons and Tamoni (2015) decompose consumption growth into different frequency-specific components. The shock of a four-year half-life explains the cross-section of returns. However, Zviadadze (2021) argues that shocks to consumption growth variance and long-run volatility explain most of the time-series variation in the interest rate. Dew-Becker and Giglio (2016) argue that persistently low-frequency shocks are most important for explaining the joint dynamics of macroeconomic fundamentals and asset returns. In more recent work, Bryzgalova and Julliard (2021) suggest that the slow-varying conditional mean of consumption growth captures the time-series variation in consumption growth and justifies the time series of stock returns.

[8] Interested parties may contact the authors directly to request access to the CMP data and corresponding replication codes. Because of a copyright agreement with Nielsen, the raw data cannot be made available online.

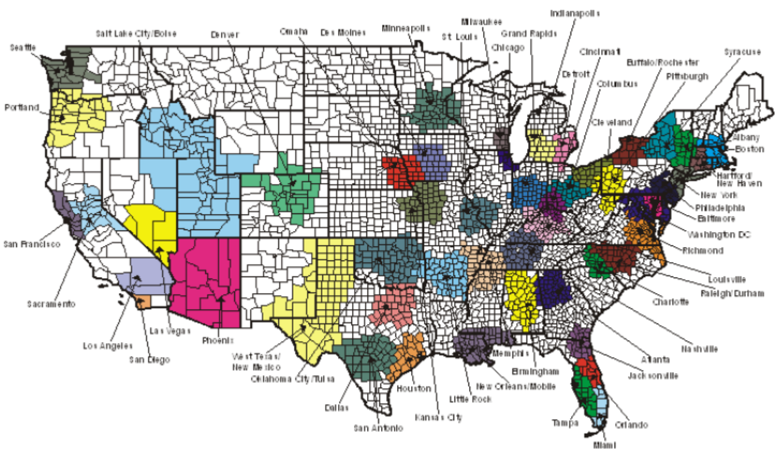
Our paper also considers the slow-varying component in the stochastic consumption growth process while focusing on conditional consumption volatility instead of the consumption means. Specifically, we investigate short-run dynamics and low-frequency volatility representing the effects of macroeconomic events. We show that both components contribute to the covariance of asset returns and consumption growth and justify the strong performance of our measure in explaining stock return variation at cross-sections.

1 Data

We use Consumer Panel Data (CPD) from the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business. CPD comprises approximately 40,000 to 60,000 households geographically dispersed and demographically balanced across the United States. This data set records the quantity and price of specific products households buy during a trip to a store on a particular day. Thus, each observation unit is the price and quantity of a particular product bought by a household during one specific trip in a day. Each product has a unique 12-digit universal product code (UPC) used to identify it. Any change in a product's attributes results in a new barcode.[9] Purchased products include groceries, drugs, small appliances, and electronics.

Figure 1: **Nielsen Market Penetration**

This figure presents 52 Nielsen-defined Scantrack markets where CPD tracks the consumption of participating households.



The markets covered by CPD consist of 52 Nielsen-defined Scantrack areas encompassing

[9]One possible concern is that a new UPC might not always represent a new product. Nielsen assigns a new UPC to previously unrecognized products; however, a product not recognized before is not necessarily new.

around 30% of household consumption in the United States (see Figure 1). CPD program participants use in-home scanners to track all the products they purchase in one trip. Tracked information includes data on prices and quantities. A trip also could mean an online purchase, in which households follow the same process of scanning the products they purchase online. The scanner given to participants is similar to what supermarkets use.

Importantly, participants also report their total expenditure on a particular trip and their spending only on grocery products tracked by a UPC. As a hypothetical example, suppose on one trip during a specific day, a household bought a gallon of milk for \$6 and a rotisserie chicken for \$30 in the supermarket. This household then spent another \$50 dining in a restaurant. As a participant enrolled in the CPD program, the household head would scan the milk and chicken for two UPC barcodes but report \$86 as the total expenditure. Therefore, CPD would have two rows for this single trip with two tracking UPCs and their prices (\$6 and \$30) and list the total expenditure as \$86 for these two rows. Unfortunately, Nielsen would not show on which activity the \$50 is spent in this example.

To ensure data quality, Nielsen implements several quality checks. First, Nielsen validates the quarterly reported consumer spending using scanner data from retailers. Second, Nielsen forms weekly sample reports to monitor outliers. Lastly, Nielsen deletes households that do not report the required minimum consumption in the past 12 months and uses various incentives to retain panelists.[10] Thus far, Nielsen has retained 80% of participating households. Nielsen carefully designs bias-free incentives, such as monthly prize drawings, gift points awarded for weekly data transmission, and sweepstakes.

To capture as many dimensions of household consumption as possible, we use the total expenditure as our raw measure for household consumption per trip in a day. Unfortunately, the sources of spending beyond those tractable UPC grocery products are unidentifiable: a dining bill, an expense for a service, or purchases of durable goods, all of which cannot be tracked and are impossible to record at the household-daily-trip-product level. CPD also provides household demographic information, such as household size, income, education, age, race, and geography. To ensure that households have the same probability of being selected regardless of household charac-

[10] Nielsen's strategies include a monthly newsletter, telecommunication, and a gift point statement (see p13 of their manual)

teristics, Nielsen assigns a projection factor or sampling weight to each household.[11] We aggregate all trips' total expenditure per household per day adjusted by its projection factor to obtain our daily total consumption measure. We deflate total daily spending based on the monthly inflation rate. We end up with 4,370 days with a total expenditure from 2004 to 2015 for the in-sample test and 1,094 days with a total spending from 2016 to 2018 for the out-of-sample test.

We link the daily consumption data to the CRSP daily stock index return to observe how the household's consumption behavior affects the stock return. To conduct cross-sectional tests, we merge our data with 25 Fama-French size and book-to-market portfolios and ten industry portfolios from Prof. Kenneth French's data library. We also combine our data with 10-size portfolios, ten book-to-market portfolios, ten investment growth portfolios, and a market portfolio used in Kroencke (2017) as a robustness check. To compare our measure's performance with other existing consumption data, we obtain consumption growth data from Kroencke (2017), hereafter unfiltered NIPA, Parker and Julliard (2005), hereafter P-J Dec-Dec, Jagannathan and Wang (2007), henceforth Q4-Q4, and Savov (2011), henceforth garbage, all from Professor Kroencke'website.[12].

We merge daily consumption data with daily stock return data after excluding weekends. However, since consumption during weekends contains a wealth of information about households' spending activities, we modify Monday's consumption growth to reflect weekend consumption information while matching Monday's stock return information.[13]

Table 1 shows the summary statistics of our daily and annualized version of daily consumption measures expressed as a percentage. Panel A shows both measures from 2004 to 2015. To facilitate comparison, we also report the summary statistics of unfiltered NIPA, three-year consumption growth (P-J), and fourth-quarter consumption (Q4-Q4) within the same sample period. Panel B reports the summary statistics for the postwar sample period (1960-2014). However, as garbage

[11]The projection factor represents the weight of each household relative to the U.S. population. In other words, the sum of the weights (projection factors) is the total household population (i.e., the number of households) in the United States. We weigh each household's daily consumption by its unique projection factor. In constructing this projection factor, Nielsen applies their proprietary linear programming optimization routine to estimate the projector weight. Consult with Nielsen at the Chicago Booth School of Business with further questions about their methodology and data collection.

[12]We thank Professor Kroencke for generously providing the data and codes to generate these data on his website (https://sites.google.com/site/kroencketim/).

[13]When we compute stock returns on Monday from an opening to close and calculate the corresponding consumption growth on Monday with Monday and Sunday's consumption, the results remain robust.

Table 1: Summary Statistics

This table, panel A, presents the summary statistics of daily consumption growth (Δc_t) and *annualized* version of daily consumption growth (Annual Δc_t). We report their mean, standard deviation, and variance. In addition, we include the autocorrelation and the correlation with the market return. We calculate the statistics of consumption growth from other consumption measures in the same sample period as our daily and annual measures. Panel B reports the summary statistics of other consumption measures in their full sample period. *Garbage data are available from 1960 to 2007. Panel C breaks down household products consumed in our data, and panel D shows the summary statistics for household characteristics.

	Panel A. Sample Period (2004-2015)					*Panel B. Sample Period (1960-2014)*			
	Δc_t	Annual Δc_t	Unfiltered NIPA	P-J Dec-Dec	Q4-Q4	Garbage*	Unfiltered NIPA	P-J Dec-Dec	Q4-Q4
Mean (%)	0.170	2.100	1.054	2.723	0.932	1.472	1.513	2.118	1.518
Standard Deviation (%)	6.164	2.239	2.199	2.810	1.252	2.973	2.618	1.385	1.980
Autocorrelation (1) (%)	-19.410	-3.839	31.210	66.950	50.250	-14.510	-8.310	80.180	21.790
Correlation with Rm (%)	2.640	7.839	73.509	59.384	69.542	19.705	33.432	39.569	39.699
Covariance with Rm (%)	0.185	0.042	0.292	0.301	0.157	0.095	0.139	0.087	0.125

Panel C. Product Breakdown	
Most instantly consumed categories, or Magnet Products: Rotisserie Chicken, Fruits, In-Store Bakes, Made-to-Order Sandwiches, etc	18.57%
Less Instantly Consumed Categories: Fresh Produce, Dairy and Yogurts, Deli Counters, Dry Grocery, Packaged Meats, Frozen Foods, and Alcoholic Beverages	57.63%
Least Instantly Consumed Categories: Non-Food Grocery and General Merchandise	14.07%
Slow-to-Consume Goods: General Merchandise	9.73%
Main Sample	100.00%

Panel D. Household Characteristics	Sample Median
Household Income	\$50,000-\$59,999
Household Size	2∼3 Members
Type of Residence	Single Family House
Male Head Age	45-49
Female Head Age	50-54
Male Head Employment	35+ Hours

data are unavailable beyond 2007, we only report summary statistics for 1960 to 2007. In addition, we summarize products consumed daily by the households in our sample.

Panel A of Table 1 indicates that next-day household spending is approximately 0.17%, lower than other annual consumption measures, such as 0.932% from Q4-Q4 or 1.054% from unfiltered NIPA (Kroencke, 2017) from 2004 to 2015. This discrepancy may be attributable to data frequency. The standard deviation of the daily consumption measure is 6.164%, signifying considerable consumption volatility in our household samples. A range of factors, including swiftly changing consumer preferences, time-sensitive promotions and discounts, seasonality and special events, susceptibility to short-term economic influences, and weather conditions, could contribute to the high volatility observed in daily consumption growth. Our consumption growth volatility is also greater than the volatility of stock market returns during the sample period, which theoretically, is possible.[14]

Notably, the correlation and covariance between our consumption growth and stock returns, although lower than other measures, are significant at the 10% and 5% levels, respectively. Our covariance is higher than that of Q4-Q4 and garbage. To substantiate the relationship between daily consumption growth and equity premium, we estimate the beta from a regression of equity premium on our consumption growth. The beta is also significant, with a t-statistic of 2.41. In aggregate, these statistics suggest a significant relationship between consumption and stock returns. Furthermore, our daily consumption displays a significantly negative autocorrelation, implying that current household spending is negatively correlated with past spending. This observation suggests a decline in household spending and a potential cautiousness in everyday expenditure.

The non-normal distribution of the daily consumption data precludes a straightforward annualization of daily moments.[15] Hence, caution is warranted when comparing the resulant annual Δc_t with other consumption measures. For example, the annual standard deviation cannot be derived based on the daily standard deviation and the number of days. Our findings reveal that the annual Δc_t exhibits lower volatility of 2.239% compared to other annual measures and has a covariance of 0.042 and a correlation of 7.839% with the excess market return. These results align with the theoretical framework presented in Section 2.1, which postulates that the variance of consumption growth is a function of both high-frequency and low-frequency variance dynamics.

Moreover, Table 1 highlights the impact of information loss from daily data aggregation into annual data, significantly reducing volatility. Specifically, the volatility of the annual Δc_t is nearly three times lower than that of the daily Δc_t. This underscores the importance of considering the limitations of annual measures derived from daily data. In light of these observations, it is crucial to recognize that the proposed daily Δc_t is specifically designed to capture the strength of daily frequency data. Therefore, annual Δc_t may not accurately reflect the underlying strength of the

[14]We appreciate the anonymous reader's comment. The volatility of consumption growth may exceed that of stock market returns due to rare, short-lived extreme conditions or events, short-term fluctuations, sampling periods, and noise or measurement errors in daily consumption growth data. Our daily data capture all of these properties (intra-annual fluctuations and short-run dynamics) as indicated in Section 2.1. Although our consumption growth has high volatility, our results confirm the relationship between consumption growth and market returns, as evidenced by significant beta, correlation, and covariance. To further mitigate potential measurement errors in consumption growth, we apply Jegadeesh et al. (2019)'s instrumental variable approach in cross-sectional regression tests.

[15]See Danielsson et al. (2006) and Kaplan (2013) for theoretical and practical discussions. We perform a Jarque-Bera test and reject the null hypothesis. This suggests that our data are not normally distributed.

daily consumption measure, as evidenced by its lower volatility, covariance, and correlation with the market compared to other measures. These findings highlight the importance of carefully considering the implications of time aggregation when analyzing financial and economic data.

Panel C of Table 1 breaks down the daily products purchased by households in our sample. The data generally comprise instantaneously consumed products and nondurable goods. For example, products that necessitate immediate consumption, such as Magnet products, constitute 19% of the sample and are frequently made to order or baked in-store. Additionally, fresh produce, dairy, or deli counters constitute 58% of the products, while less than 10% necessitate a slower consumption rate. While the average price of nondurables may be lower than that of durable goods, some nondurables, such as organic foods, are expensive and significantly impact wealth. Our nondurable goods provide support for the fundamental tenet of the CCAPM theory.

Panel D of Table 1 summarizes essential household characteristics, demonstrating that our study's sample consists of employed individuals in their early 50s who are married and reside in single-family houses with two to three members. On average, these households possess an income of approximately $60,000, which aligns with the median household income reported by the U.S. Census Bureau for 2020.[16] While this income level may seem relatively low for stock market participants, it is important to note that a substantial proportion of employed individuals invest in pensions, with 50% of pension investments allocated to equities.[17] Furthermore, the result of a 2021 Gallup poll suggests our household sample should participate in the stock market.[18] More retail investors have also invested in equities due to low transaction costs, and automatic trading platforms.[19]

Establishing a correlation between stock returns and daily consumption helps us understand these two variables' relationship. This relationship has not been explored in previous research because of the absence of daily expenditure data before CPD. In our study, we aim to fill this gap in the literature by investigating the relationship between daily stock returns and consumption.

[16]The median household income in the United States was $67,521, according to the U.S. Census Bureau's 2020 American Community Survey (https://www.census.gov/programs-surveys/acs).

[17]See Parker and Fry (2020).

[18]According to Gann et al. (2018), 89% of households with an annual income of $97,000 or more own stocks, compared to 28% of households with an income below $40,000 per year. Our sample represents households with an income level between these two groups who invest in the stock market.

[19]See the studies of the Forbes (2022) and the Bank of International Settlements (BIS (2021)).

However, it is worth noting that CPD does not provide information on households' stock market participation status or portfolio allocation choices.

To examine this link, we conduct a regression analysis of household expenditures on benchmark factors, such as the Fama-French five-factor model (FF-5), widely recognized for capturing systematic risks. Table 2, Panel A shows that all factors are statistically significant when pooling our consumption data and performing an ordinary least squares (OLS) regression. This finding has two main implications. First, we provide evidence of a positive correlation between stock returns and consumption at the daily frequency. Second, this result suggests that households in our sample consider participating in the stock market, which is consistent with the CCAPM theory.[20]

Next, we include household fixed effects to consider any time-invariant unobserved heterogeneity across households and examine the within-household variation in shopping data related to the Fama-French factors. This allows us to focus on the impact of changes in these factors on shopping behavior without the confounding effects of between-household differences. Panel B, Table 2, shows the market loses significance, but the other factors retain the sign and significance. Our result suggests that the households in our sample are attentive to fluctuations in systematic risks. At the same time, they engage in spending, thereby underscoring the relevance of our consumption data to test the CCAPM.

2 Asset Pricing with Daily Shopper Spending

2.1 A model of daily consumption dynamics

This section decomposes a time series of time-varying volatility into different components and explains how they affect the covariance between consumption growth, asset returns, and risk aversion. We fit the AR-spline-GARCH model to our data and plot each component. We conclude this section by showing the GMM results from aggregating our data into a lower frequency.

Consumption dynamics are difficult to measure in the data accurately, and their underlying stochastic process has been the subject of a long-standing debate. A common empirical practice to identify and test the stochastic consumption growth process is to use low-frequency consumption

[20] Mankiw and Zeldes (1991) consider limited market participation and show support for the CCAPM.

Table 2: Stock Market Participation Tests

In this table, we regress the daily households' consumption on Fama-French factors, including lagged common asset pricing factors, including the Excess Market Return (MKT), Small-Minus-Big (SMB), High-Minus-Low (HML), Raw-Minus-Weak (RMW) and Conservative-Minus-Aggressive (CMA). We report factor loadings and their *t-stat*. Panel A reports the results from the pooled OLS model, and panel B controls the household-level fixed effects model. Controls include household income, size, type of residence, household composition, age and presence of children, male head age, female head age, male head employment, female head employment, male head education, female head education, marital status, and TV items. *p <0.1; **p <0.05; ***p <0.01.

Panel A. Pooled OLS		
	Factor Loadings	t-stat
MKT_{t-1}	-0.043*	-1.86
SMB_{t-1}	0.241***	5.17
HML_{t-1}	0.479***	11.17
RMW_{t-1}	-0.173**	-2.19
CMA_{t-1}	0.298***	3.34
Constant	0.002***	64.39
Controls	Included	
R^2	0.153	
Observations	38,895,572	
Panel B. Household fixed effect		
	Factor Loading	t-stat
MKT_{t-1}	0.027	1.35
SMB_{t-1}	0.098**	2.36
HML_{t-1}	0.183***	4.77
RMW_{t-1}	-0.410**	-5.87
CMA_{t-1}	0.609***	7.58
Constant	1.964***	4.71
Controls	Included	
R^2	0.149	
Observations	38,895,572	

data because those are the only conventionally available data. A large fraction of the high-frequency asset returns data is lost from time aggregation in both consumption growth and stock returns in matching low-frequency consumption growth. On the other hand, aggregating the data also contaminates the consumption data.[21]

This paper demonstrates that our daily consumption data can attenuate the time aggregation bias and other statistical errors. These data enable us to explore a wealth of information in high-frequency data and further investigate the canonical consumption-based asset pricing model.

[21] Breeden et al. (1989) and Ait-Sahalia et al. (2005) show that time aggregation leads to significant errors in consumption growth and stock returns, respectively.

Bansal and Yaron (2004) and Chaudhuri and Lo (2016) imply that consumption risk produces distinct effects on financial assets over different time horizons. It is crucial to determine at which frequency the consumption risk factor operates.

Figure 2: Daily Consumption Growth

This figure plots daily consumption growth, Δc_t, from 2004 to 2015, where there is no significant trend but strong fluctuations around the mean close to zero.

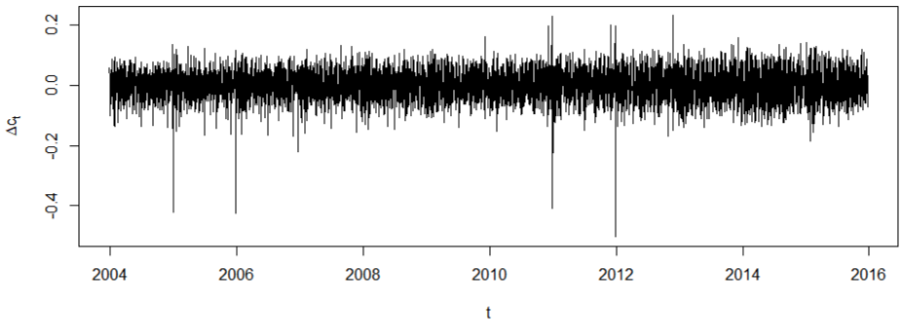


Figure 2 plots our daily consumption growth across our sample period from 2004 to 2015. We do not observe significant upward or downward time trends but strong high-frequency fluctuations around the constant level near zero, suggesting we should focus on the stochastic variance process instead of the mean.[22]

Figure 3 shows significant autocorrelations and partial autocorrelations and suggests that the autocorrelation is dominant, implying an autoregressive component instead of a moving average component should be considered in the mean process. The figure also suggests that consumption growth is negatively autocorrelated at the daily frequency, which is confirmed by the statistic in Table 1.

Considering that the presence of strong high-frequency fluctuations in time-series data and consumption usually relates to a slow-moving macroeconomic environment, one can reasonably assume that high-frequency variance has the following form:

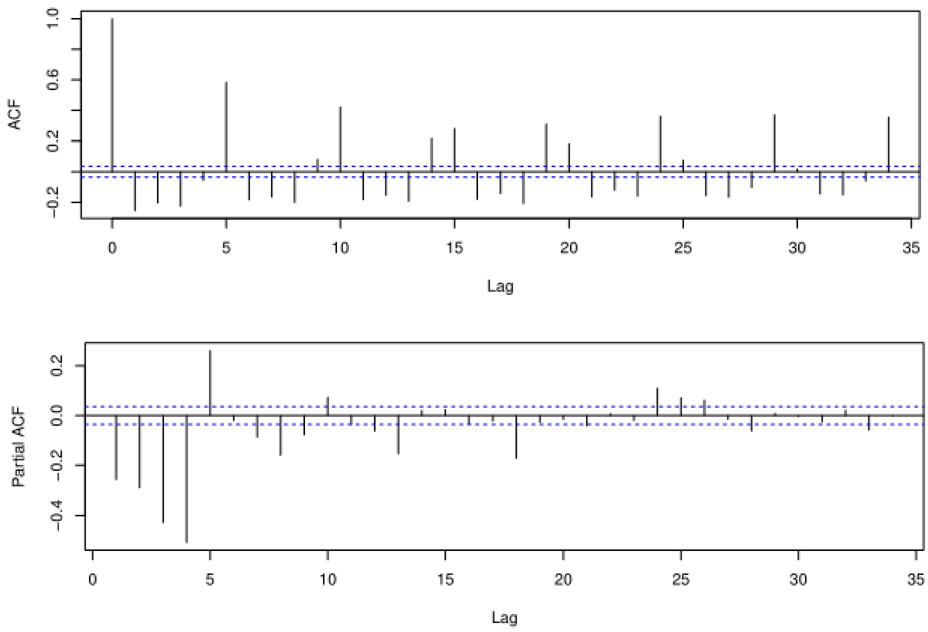
$$h_t = \tau_t g_t, \tag{1}$$

where g_t measures the short-run dynamics of high-frequency variance, and τ_t is the low-frequency

[22]The spikes might be driven by holiday spending, typified by many purchases on one day, followed by zero or fewer purchases on subsequent days.

Figure 3: Autocorrelation and Partial Autocorrelation

This figure plots the autocorrelation (ACF) and partial autocorrelation (partial ACF) of daily consumption growth (Δc_t) across different lags, suggesting an AR component should be considered in the mean process.



variance. With this form, we decompose the high-frequency volatility into two parts in the spirit of Engle and Rangel (2008).

Households continuously receive information, which can be news or noise. If the ex post information is news, the economy gradually adjusts to a new activity level. If it is noise, the economy should revert to its initial state. Therefore, the dynamics of news and noise generate short- and long-run changes in aggregate economic activity that are captured by short-run fluctuations and low-frequency volatility, respectively.

Short-run fluctuations are usually ignored in the low-frequency consumption measure. When we combine high-frequency and low-frequency consumption, any fluctuation is canceled out primarily because of the negative autocorrelation of daily consumption growth. On the other hand, low-frequency volatility determines the unconditional volatility of daily consumption growth and can be interpreted as a trend around which the conditional volatility fluctuates. Low-frequency volatility can capture the long-memory component of the volatility process associated with slowly varying, deterministic conditions in the economy or random variables that are highly persistent and move slowly.

We can write the conditional variance of consumption growth as

$$\text{var}_{t-1}(\Delta c_t) = h_{t-1}, \tag{2}$$

$$= \tau_{t-1} g_{t-1}. \tag{3}$$

Therefore, the conditional covariance between conditional consumption growth and stock returns can be written as

$$\text{cov}_{t-1}(\Delta c_t, r_{it}) = \rho \sigma_{t-1}(\Delta c_t) \sigma_{t-1}(r_{it}), \tag{4}$$

$$= \rho \sqrt{\tau_{t-1} g_{t-1}} \sigma_{t-1}(r_{it}). \tag{5}$$

To disentangle short-run dynamics from low-frequency volatility, we apply a logarithmic transformation to both sides:

$$\log(\text{cov}_{t-1}(\Delta c_t, r_{it})) = \log(\rho) + \frac{1}{2}\log(\tau_{t-1}) + \frac{1}{2}\log(g_{t-1}) + \log(\sigma_{t-1}(r_{it})). \tag{6}$$

Although logarithmic transformation is not linear, it is a monotonic function, suggesting that the proportion of low-frequency volatility and short-run dynamics in total volatility should be almost stable before and after the logarithmic transformation. Meanwhile, the central insight of the CCAPM models is that the risk level of any asset should depend on the covariance of its returns with consumption growth. If we assume that both consumption growth and stock returns are conditionally jointly lognormal, we obtain

$$E_{t-1}(r_{i,t} - r_{f,t}) + \frac{\text{var}(r_{i,t})}{2} = \gamma \text{cov}_{t-1}(\Delta c_t, r_{it}), \tag{7}$$

where $\text{var}(r_{i,t})$ is the conditional variance of asset returns. Considering this negative autocorrelation, aggregating consumption measures into a lower frequency suppresses the short-run dynamics. Based on Equation (6), we find that ceteris paribus, ignoring the short-run dynamics, will decrease $\log(\text{cov}_{t-1}(\Delta c_t, r_{it}))$, equivalently decrease $\text{cov}_{t-1}(\Delta c_t, r_{it})$, and ultimately increase the relative risk aversion coefficient γ. Therefore, short-run fluctuations could justify why daily consumption growth performs better than low-frequency consumption growth. The short-run fluctuations of less than an annual frequency make the high-frequency data superior to lower-frequency data in terms of being associated with systematic risk if the sum of the right-hand side of Equation (6) for high-frequency data is greater than that of low-frequency data.

Next, we estimate the parameters in Equation (3) for our daily consumption growth using an AR-spline-GARCH model. High-frequency volatility is decomposed into two components. One is the short-run dynamics of conditional volatility associated with the transitory effects of volatility innovations (g_t), and the other describes slower variations in the volatility process associated with more permanent effects (τ_t). This unique decomposition implies that we can separate the covariance between consumption growth and asset returns into short-run dynamics, low-frequency components, and volatility of stock returns.[23] Following Engle and Rangel (2008), we allow the data to take the functional form of this low-frequency volatility.

Here, we assume that Δc_t is consumption growth at time t and is constructed as follows:

$$\Delta c_t = \sum_{i=1}^{p} \alpha_i \Delta c_{t-i} + \epsilon_t, \quad \epsilon_t | \mathcal{F}_{t-1} \sim \mathbb{N}(0, h_t), \tag{8}$$

$$h_t = \tau_t g_t, \tag{9}$$

$$g_t = 1 + \sum_{j=1}^{n} \omega_j g_{t-j}, \quad \sum_j \omega_j = 0, \tag{10}$$

$$\tau_t = \exp(f_1(t)). \tag{11}$$

We approximate the low-frequency volatility nonparametrically using an exponential spline, which generates a smooth curve describing the low-frequency component from our daily consumption growth data. Equations (8)-(11) show that we do not impose any structure on how the macroeconomic indicators affect volatility, as the sampling frequency prevents the direct inclusion of macroeconomic variables. However, using a spline to model the low-frequency component implies a hidden structural assumption that macro effects cannot cause a sharp jump in low-frequency

[23] Boons and Tamoni (2015) and Bandi and Tamoni (2017) decompose consumption growth into parts of varying persistence and find that the shock with business cycle frequency plays a significant role in explaining the cross-section of returns. However, the high-frequency components in these papers are quarter units, whereas we focus on daily consumption growth and its volatility components.

volatility. This assumption is reasonable because sharp jumps in volatility are captured through the high-frequency component. With the imposed restriction $\sum_j \omega_j = 0$, the unconditional variance of consumption growth is

$$E(\epsilon_t^2) = \tau_t. \tag{12}$$

Therefore, the unconditional volatility of consumption growth coincides with the low-frequency volatility.

Specifically, $f_1(t)$ is a smooth function of time t, which captures the long-term trend. Using smoothing splines with smoothing parameters selected by restricted maximum likelihood, we can present $f_1(t)$, avoid the problem of knot selection, and simultaneously control for overfitting by shrinking the coefficients of the estimated function.[24]

Figure 4: Fit of the Model: Low-frequency Variance with only $f_1(t)$

This figure shows the fitted value of low-frequency variance (τ_t), which has a strong rise-and-fall pattern and suggests that a cyclical smoother ($f_2(d)$) is required. See Equations (8) to (11) for the notations and functional forms of τ_t and $f_1(d)$.

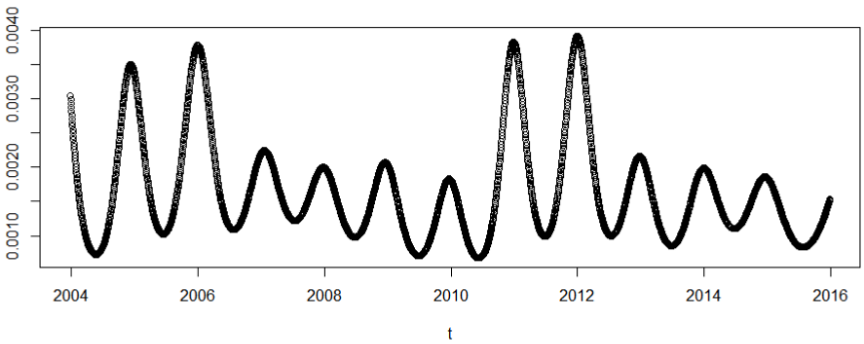


Figure 4 shows the fitted values of low-frequency variance (τ_t) with only ($f_1(d)$). The $f_1(d)$ has a very odd-looking rise-and-fall pattern, suggesting strong intra-annual fluctuations exist. We expect to see the smoothness of a long-term trend; thus, the rise and fall pattern contradicts the long-term trend definition. To address this concern, we introduce a cyclical smoother when we model low-frequency variance. We revise the low-frequency component as follows:

$$\tau_t = \exp(f_1(t) + f_2(d)), \quad d = t \bmod 250, \tag{13}$$

[24]Knot points are the points at which we expect curvature changes. Knot selection means we need to define how many knots should be in the model.

where $f_2(d)$ is a smooth function of d, representing day 1, day 2, ..., and day 250, and, therefore, characterizes the intra-annual fluctuations. We reestimate the parameters from Equations (8) to (10), and Table 3 shows the results.

Table 3: Estimation Results for the Daily Consumption Measure

This table reports the estimation results for daily consumption growth (Δc_t). Estimation is based on a model with Gaussian innovations. See model specification in Equations (8) to (10).

	Coefficient	s.e.
α_1	-0.538	0.018
α_2	-0.476	0.019
α_3	-0.490	0.019
α_4	-0.333	0.019
α_5	0.261	0.018
ω_1	0.107	0.020
ω_2	-0.080	0.020
ω_3	-0.080	0.020
ω_4	0.053	0.020

We first fit the model with the unit root test and use the maximum likelihood estimation (MLE) and Bayesian information criterion (BIC) to obtain the best autoregressive integrated moving average (ARIMA) model for daily consumption growth. The AR(5) model fits our daily consumption growth, confirming our initial guess for the mean process. For short-run dynamics of high-frequency variance, (g_t), we search for the best model by reducing it until it contains only significant terms while keeping it simple. Four lag terms meet the requirement, and all coefficients are significant. Table 3 reports the model parameter estimates and standard errors and shows they are all significant at the 1% level, suggesting that the AR-spline-GARCH model in Equations (8)-(10) fits well with our data.

Figure 5 presents the fitted value of two smooth functions ($f_1(t)$ and $f_2(d)$), and low-frequency variance (τ_t). We can see that the cyclical smoother ($f_2(d)$) picks up intra-annual fluctuations in the low-frequency volatility. The wiggle is much stronger at the beginning and end, and mild fluctuations happen during the middle of each year. The long-term trend is relatively stable but still significant. Overall, Figure 5 shows that strong intra-annual fluctuations ($f_2(d)$) exist in the low-frequency variance (τ_t).

Figure 5: Fit of the Model: Low-frequency Variance with $f_1(t)$ and $f_2(d)$

This figure plots the fitted value of two smooth functions ($f_1(t)$ and $f_2(d)$) and low-frequency variance (τ_t) in the top, middle and bottom graphs, respectively. Including $f_2(d)$ removes the rise-and-fall pattern over the long-term trend, suggesting that intra-annual fluctuations are important. See Equations (8) to (13) for our model specifications and the functional forms of $f_1(t)$, $f_2(d)$), and τ_t.

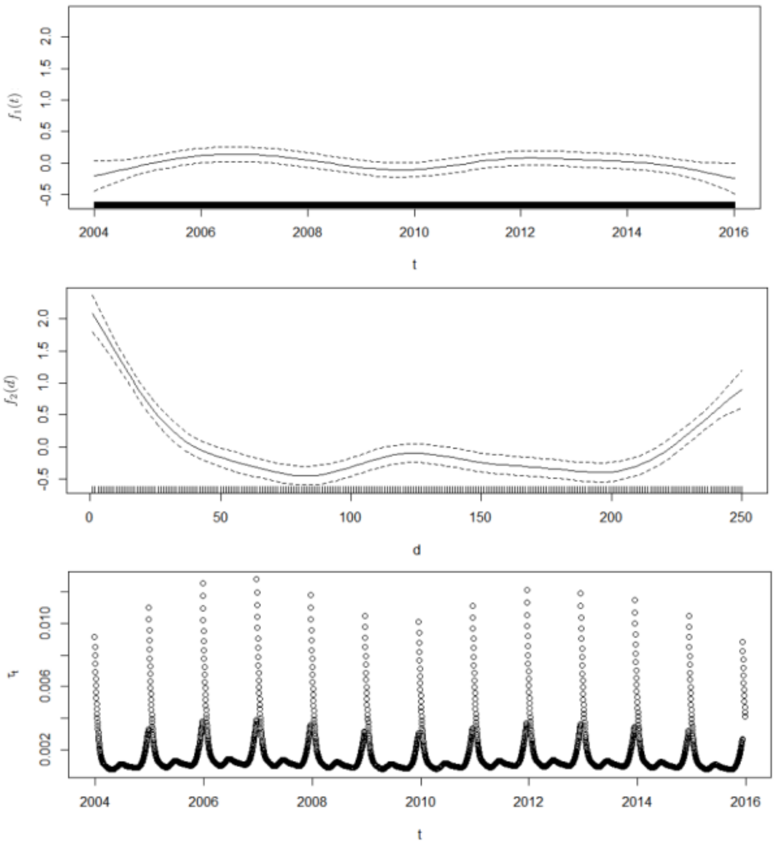


Figure 6: Fit of the Model: Low- and High-frequency Variance

This figure shows the fitted value of low-frequency variance (τ_t) in the top panel and high-frequency variance (h_t) in the bottom panel, where we find strong intra-annual fluctuations in the low-frequency variance and strong short-run dynamics in the high-frequency variance. See Equations (8) to (13) for our model specifications and functional forms of τ_t and h_t.

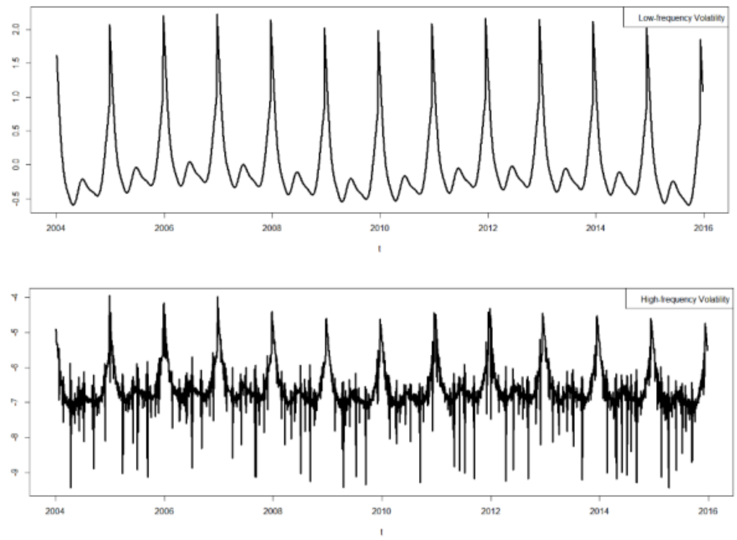


Figure 6 plots the logarithm of the fitted value of low-frequency variance (τ_t) and high-frequency variance (h_t) of our data during the sample period using the AR-spline-GARCH model. The graph shows strong intra-annual fluctuations ($f_2(d)$) and short-run dynamics (g_t). Based on the model's fit, we conclude that annual consumption growth ignores short-run dynamics and intra-annual fluctuations, as it usually has only one observation each year. The higher-frequency data have intra-annual fluctuations ($f_2(d)$) and short-run dynamics (g_t). The sum of the right-hand side of Equation (6) determines which frequency is superior to another regarding covariance.

2.2 The equity premium and risk-free rate

We consider a representative agent with additive constant relative risk aversion (CRRA) preferences in our economy. Evidence suggests that with the power utility, an implausibly high level of risk aversion is required to fit the equity premium, given that measured consumption is too smooth. This high-risk aversion also leads to a higher implied risk-free rate; thus, the equity premium puzzle is closely related to the risk-free rate puzzle. However, the increased volatility in our daily consumption measure and the positive correlation between daily consumption growth and stock returns suggest that daily consumption growth could reconcile the equity premium with reasonable risk aversion and solve the risk-free rate puzzle.

We first test the classical model using our consumption data with the Euler equation of consumption:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1}] = 0, \tag{14}$$

where C_t is daily consumption at time t, β is the subjective discount factor, γ is the relative risk aversion coefficient, and R^e_{t+1} is the next day's stock return over the daily risk-free rate. Following the literature (Hansen et al. (2008); Savov (2011)), we set β to be 0.95 and focus on γ. Given the relative risk aversion (γ) and the discount factor (β), we obtain the risk-free rate as follows:

$$R^f = E[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}]^{-1}. \tag{15}$$

Next, we report the joint test results, including the market risk premium and the risk-free rate, using the identity weighting matrix. We also report this implied risk-free rate when we test the Euler equation. As Savov (2011) and Kroencke (2017) note, this joint test puts a severe strain on the consumption-based model:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1}] = 0, \tag{16}$$

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^f_{t+1}] = 1, \tag{17}$$

where R^f_{t+1} is the gross risk-free rate. Finally, we also introduce instruments to test the conditioning information model. According to Cochrane et al. (2005), adding instruments serves two purposes. First, instruments can predict ex-post discounted returns. If the pricing model is correctly specified, we should not expect any predictability from a model, including instruments. Second, adding instruments is equivalent to testing the returns of managed portfolios. Cochrane et al. (2005) suggests that the instruments characterize the conditional distribution of returns:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1} \otimes Z_t] = 0, \tag{18}$$

where Z_t is the instrument set. We follow Kroencke (2017) and Savov (2011) and use a constant, lagged consumption growth, one plus the lagged excess market return and the detrended lagged log-price-to-dividend ratio as our instruments.

Panel A of Table 4 shows the results of a precisely identified GMM test of the Euler equation for the excess market return. The only test asset is the equity premium. Our daily measure generates a risk aversion estimate of 9.217 with a standard error of 3.03 and a risk-free rate of −0.091%. For comparison, garbage yields a risk aversion estimate of 15.63 and a risk-free rate of 17.25%. Similarly, the unfiltered NIPA matches the excess return with a relative risk aversion coefficient of 22.53 and a risk-free rate of 30.09%.

To provide more details about the GMM framework, we find that the equity premium during our sample period is significant at the 5% level.[25] As such, the significance of RRA reported above is in line with the significance of the equity premium during our sample period, lending support

[25]The t statistic is 2.05. We also find that correlation and covariance are significantly different from zero and the results are available upon request. However, due to limited space, we do not report here.

Table 4: GMM Test and Risk Aversion Estimates

This table reports the GMM test that estimates the relative risk aversion of *daily* consumption growth Δc_t. Panel A shows the GMM test for estimating the relative risk aversion coefficient from the exactly identified model. The moment restriction is as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1}] = 0.$$

Panel B shows the GMM test for estimating the relative risk aversion coefficient. In addition to the equity premium, this panel reports a risk-free rate. The moment restrictions are as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1}] = 0, \qquad E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^f_{t+1}] = 1.$$

Panel C shows the instruments of the GMM test for estimating the relative risk aversion coefficient with the instrument set Z_t containing a constant, lagged consumption growth, one plus the lagged excess market return, and the detrended lagged log-price-to-dividend ratio. The moment restrictions are as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1} \otimes Z_t] = 0,$$

where β is set to be 0.95, R^e_{t+1} is the value-weighted CRSP index return over the daily risk-free rate (r_f), γ is the relative risk aversion (RRA), *s.e* is RRA's standard error, and MAE is the mean absolute error. The implied risk-free rate is derived from RRA. The p -values are based on the J-test of over-identification conditions. Garbage, unfiltered NIPA, P-J Dec-Dec, and Q4-Q4 are the consumption growth based on Savov (2011), Kroencke (2017), Parker and Julliard (2005), and Jagannathan and Wang (2007), respectively collected from Professor Kroencke's website.

	Δc_t (2004-2015)	Annual Garbage (1960-2007)	Annual Unfiltered NIPA (1960-2014)	P-J Dec-Dec (1960-2014)	Q4-Q4 (1960-2014)
		Panel A. Equity Premium (Exactly Identified)			
RRA (γ)	9.217	15.630	22.530	42.350	64.050
(s.e.)	3.030	8.380	11.980	22.870	39.610
z-stat	3.042	1.865	1.881	1.852	1.617
MAE	0.443	0.000	0.000	0.000	0.000
Implied r_f (%)	-0.091	17.250	30.090	158.190	82.600
Observations	3021				
		Panel B. Equity Premium and Risk-Free Rate (One-Stage GMM)			
RRA (γ)	5.159	28.720	50.840	171.840	215.160
(s.e.)	0.189	9.390	12.990	48.060	58.140
z-stat	27.369	3.059	3.914	3.576	3.701
MAE	0.467	4.570	7.270	0.120	0.120
J-test *p-value*	0.232	0.630	0.390	0.120	0.550
Observations	3021				
		Panel C. Equity Premium and Instruments (One-Stage GMM)			
RRA (γ)	5.410	16.960	15.380	60.000	74.000
(s.e.)	2.452	8.150	11.040	70.000	9.000
z-stat	2.206	2.081	1.393	0.857	8.222
MAE	0.537	1.250	2.790	0.250	0.240
Implied r_f (%)	0.003	17.750	22.884	367.000	250.000
J-test *p-value*	0.598	0.950	0.960	0.250	0.240
Observations	3020				

to the CCAPM theory.[26] Our result suggests that the sampling error from the covariance between consumption growth and market excess return is unlikely to influence our analysis. Section 2 also shows cov(Δc_t,R^e) is itself significant.

Panel B augments the precisely identified model with an additional moment restriction of the risk-free rate. These two-moment restrictions force the RRA to match our daily consumption measure with excess return and a traded risk-free Treasury-bill asset. The relative risk aversion coefficient is 5.159 with a standard error of 0.189. Compared with other measures in this context, our RRA is the lowest. In addition, we run the J-test, whose null hypothesis is that the model is not over-identified. The p-value is not significant, thus indicating that the one-stage GMM model that jointly tests equity premium and the risk-free rate is identified correctly.

Panel C uses the instruments to condition information at time $t-1$. When we view the instrumented returns as managed portfolios (Cochrane et al. (2005)), the relative risk aversion coefficient is 5.41, the lowest value of all the measures. This result reconciles the difference in risk aversion estimates between the household finance and empirical asset pricing literature. The household finance literature usually considers a relative risk aversion coefficient of less than 10, while the empirical asset pricing literature considers a relative risk aversion coefficient greater than 10. Meanwhile, the implied risk-free rate is 0.003%, a value closest to the empirically observed average risk-free rate.[27] The mean absolute error of moment restriction increases to 0.537%, which could be attributed to the return predictability of the instruments, which are known to be good predictors (Goyal and Welch (2008)). Moreover, the p-value of the J-test is insignificant, indicating that this model is well-identified.

Overall, we find that the daily consumption measure explains well the equity premium with a modest relative risk aversion coefficient. Once the risk aversion coefficient is calibrated to the consumption data, the resultant risk-free rate is considerably lower than those obtained using traditional annual consumption measures. This superior performance of our daily measure can be attributed to its higher frequency and volatility, as we have elucidated in Section 2.1.

[26] Based on the linearized version of the CCAPM, E[R^e]=RRA$\times$cov(Δc_t,R^e), which suggests RRA=E[R^e]/cov(Δc_t,R^e), where R^e is the excess market return or equity premiuim and RRA is relative risk aversion. If cov(Δc_t,R^e) were known, the estimated RRA would be proportional to the average excess market return, and the significance of RRA should imply the significance of the average excess market return. Our equity premium is significant, as reported in footnote 25, consistent with the significance of RRA in Table 4.

[27] In our sample period, the observed risk-free rate was 0.005% on average.

2.3 The cross-section of returns

Next, we perform the Fama and Macbeth (1973) regression to test whether our Δc_t can explain the variation of stock returns cross-sectionally. The basic one-factor return-beta representation is

$$E[R^e_{i,t+1}] = \lambda + \lambda_c \beta_i, \tag{19}$$

where the left-hand side is the expected excess return per period of testing asset i; λ is a pricing error, which should be zero (risk-fee rate) if excess returns (raw returns) are the dependent variable; and λ_c is the price of consumption risk that measures the risk premium per unit exposure to consumption risk.

We first perform a time-series regression on monthly excess asset returns to obtain the time-varying consumption beta:

$$R^e_{i,t+1} = \alpha_i + \beta_{i,c} \log(\frac{C_{t+1}}{C_t}) + \epsilon_{i,t+1}. \tag{20}$$

Doing so allows the first path to vary across months, as Cochrane et al. (2005) suggested. Then we run cross-sectional regressions of excess asset returns on their consumption betas during each period:

$$E[R^e_{i,t+1}] = \lambda_c \beta_{i,c}. \tag{21}$$

Each month, we get λ_c or the price of risk as specified in Fama and Macbeth (1973).

As the standard tests for cross-sectional asset pricing, we first use three decile portfolios independently sorted by size, a book to market, and investment, in addition to a market portfolio, as our 31 portfolio testing assets. Next, we choose the 25 Fama and French (1993) size and book-to-market portfolios, plus another ten industry portfolios to increase the dimensionality of the cross-section and address the concerns raised by Lewellen et al. (2010). This selection of two testing asset groups (31 and 35 portfolios) shows an economically significant cross-section. Jensen et al. (1972) raise concerns about the first-stage betas being measured with errors; thus, using portfolios as test assets is better.

Utilizing portfolios as test assets, however, is associated with certain limitations. One prominent challenge pertains to the reduction in test power resulting from the diminished dimensionality associated with using portfolios. That is to say, the mean returns of portfolios are subject to changes in fewer explanatory factors than individual stocks. Furthermore, portfolio diversification might mask cross-sectional phenomena in individual equities that are irrelevant to the portfolio grouping process.

Another unsettling effect of portfolio masking concerns the cross-sectional relationship between average returns and betas. The single-factor CAPM model, for instance, is based on the precise linear relationship between expected returns and betas, which holds if the market index utilized for computing betas is positioned on the mean/variance frontier of the universe of individual assets. A rejection of this linear relationship suggests that the index is not positioned on the frontier. However, if the individual assets are consolidated into portfolios sorted by beta, any asset pricing errors across individual assets unrelated to the beta are unlikely to be identified. Thus, this technique could yield an incorrect inference if the index is situated on the efficient frontier generated using beta-sorted portfolios.

We utilize individual stocks to overcome the limitations of employing portfolios as testing assets. However, the Fama-MacBeth regression method is susceptible to an EIV bias when testing asset pricing models. We employ the instrumental variable (IV) approach to mitigate this bias, as suggested by Jegadeesh et al. (2019). Jegadeesh et al. (2019) use monthly data and separate monthly samples into odd and even months. Since our data is daily, we partition the entire sample into subsamples based on odd- and even-numbered days of the week, where odd days include Monday, Wednesday, and Friday. In contrast, even days include Tuesday and Thursday. We then perform separate time-series regressions for the odd- and even-numbered month subsamples to estimate the betas for each asset during both odd- and even-numbered months.

With the odd-numbered day betas as IV betas and even-numbered day betas as EV (evaluation variable) betas, we construct the matrices for the betas of all assets: $\hat{B}_{IV}$ and $\hat{B}_{EV}$, where B is the $N \times (K+1)$ matrix containing all the betas augmented by a vector of one, that is, $B = [1, \beta]$, where one is an $N \times 1$ vector of ones.

Then we estimate a cross-sectional IV regression. That is, for each even-numbered day t, we run a cross-sectional regression, and the factor-mimicking portfolio (FMP) at time t can be written as

$$\hat{\gamma}_t = (\hat{B}_{IV}\text{'}V^{-1}\hat{B}_{EV})^{-1}\hat{B}_{IV}\text{'}V^{-1}R_t,$$

where R_t is the excess return for even-numbered days and is an $N \times 1$ vector, and $\hat{\gamma}_t$ is a $(K+1) \times 1$ matrix containing all estimated FMPs augmented by mispricing in the first column. We take the betas in the even-numbered day subsample as the IVs for each odd-numbered day and estimate the same regression to obtain the FMP.

To perform the IV method, we utilize daily returns from both odd- and even-numbered days over a rolling one-year estimation period in the same vein as Jegadeesh et al. (2019) to estimate betas so that the measurement error in the instrumental variable and explanatory variables are not correlated cross-sectionally.[28] We fit the second-stage cross-sectional regression each day using the IV estimator.

We follow Gu et al. (2020) screening criteria to select stocks. Additionally, we include the market value of equity and the book-to-market ratio as controls, as suggested by Boguth and Kuehn (2013). Considering that the results remain qualitatively similar and including intercept terms is a more standard procedure (Lettau and Ludvigson (2002); Jagannathan and Wang (2007)), we only report the results with the intercept.[29]

In model (1), Table 5, panel A, we report the results of cross-sectional tests using those mentioned above 31 portfolios as testing assets. The λ_c is 1.289%, which is significant at the 5% level, suggesting that for one unit of risk exposure to households' daily consumption risk, the risk premium increases by 1.289% per day. The mean absolute pricing error is 0.034% for daily returns. In models (2) to (4), we control for excess market return, small-minus-big factor return, high-minus-low, conservative minus aggressive, and robust-minus-weak. The measures for λ_c are consistently positive and significant at the 5% level. These results suggest that our daily consumption measures can explain the cross-section of returns. Furthermore, the consumption risk premiums are all positive and range from 0.739 to 1.289 across different specifications. This implies that investors consistently command a premium to hold assets with high consumption risk

[28]Jegadeesh et al. (2019) apply three-year rolling window beta estimation. They can afford to use the long windows as their data started in 1956.

after controlling for other common risk factors.

In Panel B, we run cross-sectional regressions using testing assets of 25 portfolios sorted on size and book-to-market and ten industry portfolios. The results are qualitatively the same. In model (1), λ_c is 1.668%, which is about 30% larger than that from using the 31 portfolios as testing assets, and all the remaining λ_c in the model (2)-(4) are significant at the 5% or 10% level, indicating a positive return and consumption beta relationship.

[27] The results are available on request.

[28] We use the formula $4(\frac{T}{100})^{\frac{2}{9}}$ to find the optimal number of lags for the Newey-West t-statistics.

Table 5: Fama-MacBeth Cross-Sectional Regressions: *Daily* Consumption Growth's Price of Risk and Portfolios as Testing Assets

This table reports the Fama-MacBeth two-pass cross-sectional regressions using portfolios as testing assets. Δc_t denotes our daily consumption growth. Panel A uses 31 portfolios separately sorted by size, book-to-market, investment, and one market portfolio over a risk-free rate. Panel B uses 25 Fama and French (1993) portfolios sorted by size, book-to-market, and ten industry portfolios. For all models, we use nine-lag Newey-West t-statistics.[30] We also report the mean absolute pricing error (MAPE). The sample period is from 2004 to 2015. *p <0.1; **p <0.05; ***p <0.01.

Panel A. 31 Portfolios

	(1)	(2)	(3)	(4)	(5)
Δc_t	1.289**	1.208**	0.739**	0.810**	
	(0.573)	(0.479)	(0.371)	(0.375)	
MRF		0.006	0.029	0.045*	0.043*
		(0.026)	(0.027)	(0.024)	(0.024)
SMB			-0.002	0.006	0.006
			(0.009)	(0.009)	(0.009)
HML			-0.005	-0.001	-0.002
			(0.011)	(0.011)	(0.011)
CMA				0.010	0.010
				(0.010)	(0.010)
RMW				-0.004	-0.002
				(0.006)	(0.006)
UMD				0.070***	0.065***
				(0.025)	(0.024)
Constant	0.035*	0.026	0.004	-0.012	-0.010
	(0.018)	(0.020)	(0.023)	(0.018)	(0.019)
Observations	93,651	93,651	93,651	93,651	93,651
R^2	0.125	0.331	0.503	0.670	0.645
MAPE	0.034	0.001	0.000	0.001	0.001

Panel B. 35 Portfolios

	(1)	(2)	(3)	(4)	(5)
Δc_t	1.668***	1.394**	0.777*	0.658*	
	(0.612)	(0.526)	(0.391)	(0.383)	
MRF		-0.053	0.006	-0.076	0.003
		(0.050)	(0.020)	(0.052)	(0.028)
SMB			-0.003	0.007	0.003
			(0.008)	(0.011)	(0.009)
HML			-0.007	-0.054*	-0.000
			(0.007)	(0.028)	(0.011)
CMA				0.045***	0.010
				(0.017)	(0.009)
RMW				0.023	0.004
				(0.015)	(0.008)
UMD				0.101***	0.068***
				(0.029)	(0.025)
Constant	0.043**	0.068**	0.033*	0.078**	0.032
	(0.018)	(0.028)	(0.017)	(0.035)	(0.021)
Observations	105,735	105,735	105,735	105,735	105,735
R^2	0.135	0.304	0.488	0.655	0.636
MAPE	0.035	0.000	0.001	0.001	0.001

Table 6: Fama-MacBeth Cross-sectional Regressions: Individual Stocks as Testing Assets

This table reports the Fama-MacBeth two-pass cross-sectional regressions using individual stocks as testing assets. Δc_t denotes our daily consumption growth. Betas for each day are estimated using daily returns data over the previous year, and cross-sectional regressions are fitted using the IV and OLS methods. We include the log-transformed market value of equity and book-to-market ratio to control for individual stocks' characteristics and size differences in each model. For all models, we use nine-lag Newey-West t-statistics. We report the mean absolute pricing error (MAPE). The sample period is from 2004 to 2015. *p <0.1; **p <0.05; ***p <0.01.

	Individual Stocks				
	(1)	(2)	(3)	(4)	(5)
Δc_t	0.458***	0.496***	0.257***	0.320***	
	(0.130)	(0.088)	(0.079)	(0.067)	
MRF		0.007	0.013	0.028***	0.031**
		(0.012)	(0.010)	(0.008)	(0.013)
SMB			-0.008	-0.000	0.002
			(0.006)	(0.003)	(0.005)
HML			-0.020***	-0.013**	-0.011
			(0.007)	(0.006)	(0.006)
CMA				0.010**	0.005
				(0.004)	(0.003)
RMW				-0.004*	-0.007*
				(0.003)	(0.005)
UMD				0.076***	0.073***
				(0.006)	(0.010)
log(Market Value of Equity)	0.000	0.001	0.001	-0.000	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Book to Market Ratio	-0.000***	-0.000	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.023	0.027***	0.030***	0.008	0.010
	(0.016)	(0.007)	(0.008)	(0.008)	(0.008)
Observations	11,116,267	11,056,111	11,115,895	11,115,255	11,110,597
R^2	0.010	0.018	0.037	0.046	0.043
MAPE	0.020	0.006	0.009	0.003	0.003

We repeat the cross-sectional regression with individual stocks as testing assets and report the results in Table 6. In model (1), λ_c is 0.458% in the one-factor model, which is lower than the portfolio models and might be individual stock returns are more volatile than the portfolios. All λ_c in models (1)-(4) are positive and significant at the 1% level, indicating that our daily consumption explains the cross-sectional variation in individual asset returns after addressing the error-in-variable bias.

In addition, we extend our testing assets to the 167 portfolios used by Giglio and Xiu (2021)

[31]. We repeat the regressions in models (1) and (4) using these assets, and all $\lambda_c s$ are significant at the 5% level. We do not report these results here to save on space, but they are available on request.

2.4 Consumption-mimicking portfolio tests from 1960 to 2015

Our sample period is from 2004 to 2018, and the prior sample period is between 2004 and 2015, implying the out-of-sample period is between 2016 and 2018. However, 15 years of data do not represent a long time panel; other annual consumption measures often date back to 1960 or 1926. Most papers in this literature perform the pricing test using the data from 1960 to avoid the confounding effect of the recessions. To better apply the traded version of our daily consumption series and make a fair comparison with other consumption measures, we form the consumption-mimicking portfolio (henceforth, CMP) and extend this traded version of our daily consumption series back to 1960.[32]

We aggregate our daily CMP at the annual frequency and compare its performance with other annual consumption measures from 1960 to 2014 when these measures have available data.[33] Later, in Section 5.2, we will show the performance of our CMP at a daily frequency from 2004 to 2015, our in-sample period.

The mimicking portfolio approach can alleviate the inflated price of risk because of the measurement errors of nontradable assets. We can write this as

$$\Delta c_t = \text{CMP}_t + \varepsilon_t, \tag{22}$$

where Δc_t is consumption growth, CMP is consumption-mimicking portfolios, and $cov(R_t, \varepsilon_t) = 0$ for any excess return, R_t. The term ε_t is noise and orthogonal to the returns; therefore, it deflates the beta estimates and the estimated risk price (see Adrian et al. (2014); Pukthuanthong et al. (2021)).

[31]The 167 portfolios come from a subset of the testing assets used by Giglio and Xiu (2021). We do not include them because these 167 portfolios are *all* we can find in Professor Ken French's library. They include 25 portfolios sorted on size and operating profitability, 25 on size and momentum, two sets of 25 on size and short-/long-term reversal, 25 on operating profitability and investment, 25 on size and book-to-market, and 17 on industry portfolios.

[32]We thank Professor Alexi Savov for this suggestion.

[33]To alleviate the aggregation bias, we use the fourth-quarter year-over-year CMP as our annual growth measure.

It is noteworthy that ε_t does not affect the covariances between returns and Δc_t and thus should not affect our cross-sectional result and R^2. The presence of ε_t will attenuate the time series β of every asset by a factor of $var(\Delta c)/var(\text{CMP})$, the amount by which the cross-sectional price of risk (λ) is inflated to precisely compensate for the reduction in the time-series β.

Our study performs the CCAPM test using a CMP compared with other measures in this section and a robustness check in Section 5.2. To construct the CMP, we project our Δc_t onto the space of excess returns using the following time-series regression:

$$\begin{aligned}\Delta c_t =& \Phi + \Gamma'[\text{BL, BM, BH, SL, SM, SH, MOM, LTGovBond},\\ &\text{MTGovBond, STGovBond, LowGradeCorpBond}]_t + \epsilon_t,\end{aligned} \tag{23}$$

where the set [BL, BM, BH, SL, SM, SH, MOM] consists of the excess returns of the six Fama-French benchmark portfolios on size (Small (S) and Big (B)) and book-to-market (Low (L), Medium (M), and High (H)) over the risk-free rate, and MOM is the momentum factor. We collect the returns of long-term bonds (LTGovBond, >10 years), medium-term bonds (MTGovBond, 1 to 10 years), short-term government bonds (STGovBond, ≤1 year), and low-grade or high-yield corporate bonds (LowGradeCorpBond), respectively, from Datastream. We choose these returns as researchers commonly apply them and span the space of stock and bond returns. Ideally, the ϵ_t is orthogonal to the space of returns so that the covariance of any asset with Δc_t is identical to its covariance with the CMP.

We normalize the weights, Γ, to sum to one to make the units convenient. The CMP return is fitted value from the following regression:

$$\begin{aligned}\Delta c_t =& \hat{\Phi} + \hat{\Gamma}'[\text{BL, BM, BH, SL, SM, SH, MOM, LTGovBond},\\ &\text{MTGovBond, STGovBond, LowGradeCorpBond}]_t,\end{aligned} \tag{24}$$

and $\hat{\Gamma} = \frac{\Gamma}{\sum \Gamma}$ using OLS from the daily data from 2004 to 2015. We embrace the time-series approach introduced by Lamont (2001), who introduced this common approach for mimicking portfolio constructions. We multiply normalized weights ($\hat{\Gamma}$) by the projected assets and sum them to generate a daily measure of consumption growth back to 1960.

Table 7 shows the GMM tests in a precisely identified model. We first report the annual CMP from 1960 to 2015, where the latter year is the end of our primary sample. We find that the RRA is 7.24 with a risk-free rate of 17.302%. Second, to better compare our annual extended CMP with other existing measures, we tailor our sample to be the same as the other measures from 1960 to 2014. The third column of Table 7 reports an RRA of 7.477, which is lower than all other annual consumption measures in the same sample period. In addition, the implied daily risk-free rate is 18.33%, which is slightly higher than that of the garbage but significantly lower than those of unfiltered NIPA, P-J, and Q4-Q4.

Table 7: GMM Test: *Annual* Consumption Mimicking Portfolio

In this table, we extend the daily consumption measure back to 1960 to better compare its performance with other existing measures. We construct the consumption-mimicking portfolios (CMP) using the approach described in Section 2.3. We additionally report the GMM test for the annual CMP from 1960 to 2014 and results for other measures in the same period. Annual Δc_t CMP, Garbage, unfiltered NIPA, P-J Dec-Dec, and Q4-Q4 are the consumption growth based on our consumption growth CMP, Savov (2011), Kroencke (2017), Parker and Julliard (2005), and Jagannathan and Wang (2007), respectively collected from Professor Kroencke's website.

Equity Premium (Exactly Identified)	Annual Δc_t CMP	Annual Δc_t CMP	Garbage	Unfiltered NIPA	P-J Dec-Dec	Q4-Q4
	1960-2015	1960-2014	1960-2007	1960-2014	1960-2014	1960-2014
RRA (γ)	7.240	7.477	15.630	22.530	42.350	64.050
(s.e.)	2.934	3.098	8.380	11.980	22.870	39.610
z-stat	2.470	2.410	1.865	1.881	1.852	1.617
MAE	0.007	0.007	0.000	0.000	0.000	0.000
Implied r_f (%)	17.302	18.330	17.250	30.090	158.190	82.600

Next, we perform the Fama-MacBeth two-path cross-sectional regressions to test whether this prolonged annual CMP carries a risk premium. We use the standard sample from 1960 to 2015 instead of 1960 to 2014 in Table 8.

In panels A and B of Table 8, we present results using 31 and 35 portfolios from annual CMP consumption controlling for the Fama-French five-factor plus a momentum factor. Only model (9) using 35 portfolios shows a weakly positive risk premium. Admittedly, the performance of the CMP in explaining the cross-section of stock returns is inferior to its original daily measure. As argued in Section 2.1, the annual aggregation might dilute the information from our daily consumption measure, thus significantly limiting its ability to test the risk premium.

Table 8: Fama-MacBeth Cross-sectional Regressions: *Annual* CMP, 1960-2015

This table reports the prices of risk from the Fama-MacBeth regressions on extended consumption-mimicking portfolios (CMP) aggregated from daily CMP and Fama and French (2018)'s six factors. Annual CMP Δc_t denotes our daily consumption growth in the CMP aggregated into annual frequency from 1960 to 2015. Panel A presents the results based on the testing assets of the 31 portfolios, including ten size-sorted, ten book-to-market-sorted, ten investment-sorted portfolios, and one market portfolio. Panel B presents the results from the portfolio's testing assets, including the 25 size- book-to-market-sorted and ten industry portfolios. We report four-lag Newey-West t-statistics in brackets and the mean absolute pricing error as MAPE for all models. *p <0.1; **p <0.05; ***p <0.01.

	Panel A 31 Portfolios					*Panel B 35 Portfolios*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Annual CMP Δc_t	-0.059	-0.045	-0.173	0.425	0.406	-0.326	-0.294	-0.209	0.494*	0.353
	(0.200)	(0.203)	(0.186)	(0.297)	(0.335)	(0.209)	(0.215)	(0.188)	(0.294)	(0.314)
MRF	-0.000	0.004	-0.032	0.006		-0.084**	-0.068	-0.049	-0.029	
	(0.041)	(0.037)	(0.043)	(0.052)		(0.041)	(0.041)	(0.036)	(0.042)	
SMB	0.034	0.034	0.032			0.039	0.036	0.036		
	(0.024)	(0.024)	(0.025)			(0.024)	(0.025)	(0.024)		
HML	0.036*	0.035*	0.036			0.041**	0.042**	0.039**		
	(0.018)	(0.019)	(0.019)			(0.017)	(0.017)	(0.017)		
RMW	0.023**	0.023**				-0.001	-0.005			
	(0.010)	(0.010)				(0.018)	(0.017)			
CMA	-0.020	-0.019				0.018	0.024			
	(0.021)	(0.021)				(0.016)	(0.017)			
UMD	-0.022					-0.047				
	(0.040)					(0.041)				
Constant	1.057***	1.053***	1.084***	1.061***	1.055***	1.132***	1.117***	1.100***	1.102***	1.065***
	(0.037)	(0.031)	(0.040)	(0.048)	(0.020)	(0.033)	(0.033)	(0.029)	(0.036)	(0.019)
R^2	0.722	0.696	0.625	0.423	0.261	0.694	0.662	0.582	0.389	0.215
MAPE	0.354	0.325	0.357	0.027	1.002	0.670	0.657	0.561	0.022	1.000

2.5 Kleibergen and Zhan (2020) test

The work of Kleibergen and Zhan (2020), hereafter referred to as KZ, calls into question the validity of utilizing consumption growth measures to identify beta. KZ contend that, in the first pass of the Fama-MacBeth regression, all betas should be statistically distinct from zero, a criterion that may not be satisfied when the number of testing assets is close to the number of time-series observations. This is commonly known as the "Limited T vs. Large N" problem. If the betas are jointly zero or display no variation, the risk premium will be subject to bias. The literature predominantly utilizes annual consumption measures from the postwar era of 1960. Consequently, the most frequently used testing assets comprise 30 to 45 portfolios, leaving few degrees of freedom for robust inference tests.

To test the sufficiency of portfolio loadings of Δc_t in identifying the factor risk premium in the second-pass regression, we adopt the test statistic introduced by KZ. As per KZ, identifying the risk premium is tantamount to testing the null hypothesis that the test portfolio factor betas are zero. KZ propose a rank test to scrutinize the variation in the first-path betas under the null hypothesis that they are jointly zero. Our study applies this test to P-J, Q4-Q4, garbage, and unfiltered NIPA, revealing that only garbage successfully passes the rank test.[34]

Table 9: Kleibergen and Zhan (2020) Tests

This table reports Kleibergen and Zhan (KZ) test results. We provide the p-value of KZ's rank test, based on an F-test of the null hypothesis that the factor exposures, or betas, from the first pass of Fama-MacBeth regression, are jointly zero. Δc_t, Garbage, NIPA, P-J Dec-Dec, and Q4-Q4 are the consumption growth based on our consumption growth, Savov (2011), Kroencke (2017), Parker and Julliard (2005), and Jagannathan and Wang (2007), respectively collected from Professor Kroencke's website. 31 portfolios include ten size-sorted, ten book-to-market-sorted, ten investment-sorted portfolios and one market portfolio. Thirty-five portfolios include the 25 size- and book-to-market-sorted and ten industry portfolios. We select individual stocks using the same screening criteria as Gu et al. (2020).*p <0.1; **p <0.05; ***p <0.01.

Testing Assets	Δc_t (2004-2015)	Garbage (1960-2014)	Unflitered NIPA (1960-2014)	PJ Dec-Dec (1960-2014)	Q4-Q4 (1960-2014)
31 Portfolios	0.000***	0.006***	0.211	0.531	0.273
35 Portfolios	0.000***	0.520	0.923	0.651	0.791
Individual Stocks	0.073*	0.426	0.136	0.535	0.436

Table 9 presents the application of the KZ rank test to our measure, utilizing 31, 35, and individual stocks as testing assets, which we also employ in the Fama-MacBeth two-path regression in Tables 5 and 6. Our measure passes the rank test in all sets of testing assets. Specifically, the p-values from the 31 and 35 portfolios suggest that our first-path betas are not jointly zero. The test results for our measure are not adversely affected by the small N issue typical of high-frequency data. Our measure also passes the KZ test when we employ individual stocks, which is a significant milestone given that individual stocks are the most demanding threshold for any factor to price (Jegadeesh et al. (2019)).

For individual stocks, the p-value rises to .073, rejecting the null at the 10% level. We also conduct individual stock tests for other annual measures. However, because of the variation in the samples used in the daily and annual measures, we cannot use the same set of individual stocks for our daily and annual measures. For other annual measures, we adopt the T/N ratio of three (3) based on Kleibergen and Zhan (2020) the number of periods and individual stocks to determine the number of stocks to use. Our annual measures have a T of 54 from 1960 to 2014 and 47 for garbage. Thus, we select 18 stocks (54/3) for other measures and 16 (47/3) for garbage ranked by

[34]See table III in Kleibergen and Zhan (2020), where they use 31 portfolios as testing assets.

PERMNOs with non-missing observations during the sample period. We use PERMNO as it is a characteristic that is, for practical purposes, assigned randomly by CRSP. None of the p-values of the rank tests for other measures is significant.

3 Magnet Products, as well as Nonfood Grocery and General Merchandise

This study section exploits our data set's rich granularity, allowing us to examine over two million products. Campbell (2018) suggests testing the consumption-based asset pricing model necessitates using instantaneous consumption data instead of data on relatively slow-moving consumption. To this end, we focus on a subset of products tracked by Nielsen, called Magnet products, which do not possess regular UPCs and are generally perishable and considered strictly nondurable goods. We anticipate that the model using only spending on Magnet products will yield a lower estimate of the risk aversion coefficient since they are purely nondurable and require immediate consumption.

In addition to examining Magnet products, we compare their performance to products with the opposite characteristics, specifically those that can be stored for extended periods, such as non-food grocery and general merchandise.[35] We define the latter as relatively durable goods from two perspectives: first, specific components of these products are typically nondurable, while most can be classified as durables, and second, the time between successive purchases is significantly shorter than that for typical durables, such as furniture and mobile homes sold in retail chains.

The model with spending on relatively durable goods should perform worse than the one with only spending on Magnet products. This expectation also aligns with the results of Yogo (2006), which investigates the CCAPM with durable goods and assumes households derive utility from the service flow of durable goods that is a constant fraction of the stock. He finds that the durable consumption model requires a high level of risk aversion to fit the high level and volatility of expected stock returns compared with nondurable goods.

[35] These products include detergent, diapers, fresheners/deodorizers, household cleaners, laundry supplies, pet care, batteries/flashlights, candles, computer/electronic, cookware, film/cameras, insecticides, lawn and garden, motor vehicles, and office supplies, all of which can be considered to be semidurable goods in our data.

We test our hypothesis by applying each household's consumption activities on Magnet products and relatively durable goods. The caveat is that Nielsen did not collect data on Magnet products until 2007. Even during that year, such products were sparsely reported because of the inadequate recognition of their existence. Yet the sample period of Magnet (2007-2015) would be inconsistent with others (2004-2015). Therefore, we conduct our tests in two ways that accommodate consistency and precision. We first use the primary sample that ends in 2015, which renders a shorter sample period for Magnet products (2007-2015) compared to relatively durable goods and the primary sample (2004-2015). Next, to create the same sample for all without sacrificing the length of the data period, we choose 2007 as the starting point and 2018 as the ending point for all three product groups (Magnet, Relatively Durable Goods, and Main Sample), thereby ensuring a fair comparison from 2007 to 2018. In Table 10, panels A and B, we report primary and extended results.

Table 10 shows the results and confirms our expectations. In panel A, we first report that spending on relatively durable goods correlates more closely with the excess market return than Magnet products. Meanwhile, the model with spending on Magnet products generates the lowest estimate for the risk aversion coefficient of 7.96 with a 10% significance level compared to 9.698 and 9.217 at the 1% significance from relatively durable goods and all products from the primary sample. This lower relative risk aversion coefficient generated by the consumption of Magnet products relative to the consumption of relatively durable goods is consistent with Campbell (2018)'s argument and supports our initial prediction.

However, panel A also shows a negative covariance and correlation between Magnet product consumption and excess market returns. This abnormal coefficient might be attributed to the sparsity of Magnet products consumption data. As discussed, Nielsen does not fully report Magnet products during 2007, and only eight years of data are available in panel A, which might introduce noise to Magnet consumption growth. When we extend the data to 2018, the covariance and correlation of Magnet consumption have become positive, as shown in panel B. Meanwhile, the risk aversion coefficients have the same pattern as in panel A, further supporting our hypothesis.

Table 10: Magnet Products, and Nonfood Grocery and General Merchandise

This table presents the descriptive statistic of daily consumption growth, Δc_t, of magnet products, relatively durable goods, and all products in our database, similar to Table 4 (main sample). Nielsen defines magnet products as products that do not have regular UPCs. Relatively durable goods, including nonfood groceries and general merchandise, have the opposite quality or those that can be stored for a long time. We present relative risk aversion (γ), its corresponding standard errors, *z-statistics*, and implied risk-free rate (r_f). β is set to 0.95. R^e_{t+1} is the value-weighted CRSP index return over the daily risk-free rate. See the estimation method described in Section 2.2 and Table 4. Panels A and B present the result from the sample ending in 2015 and 2018, respectively.

Panel A: Sample ending 2015			
	Magnet Products (2007-2015)	Relatively Durable Goods (2004-2015)	Main Sample (2004-2015)
Mean	0.269%	0.302%	0.170%
Standard deviation	8.505%	9.830%	6.164%
Correlation with Market	-0.950%	1.100%	2.640%
Covariance with Excess Market Return	-0.110%	0.120%	0.185%
RRA (γ)	7.960	9.698	9.217
(s.e.)	4.274	2.288	3.030
z-stat	1.862	4.239	3.042
Implied r_f	-0.170%	-0.440%	-0.091%
Observations	2258	3021	3021
Panel B: Sample ending 2018			
	Magnet Product (2007-2018)	Relatively Durable Goods (2007-2018)	Main Sample (2007-2018)
Mean	0.250%	0.240%	0.127%
Standard deviation	8.360%	9.360%	5.778%
Correlation with Market	0.010%	1.250%	2.980%
Covariance with Excess Market Return	0.700%	0.880%	19.770%
RRA (γ)	8.666	9.604	9.784
(s.e.)	3.323	2.662	4.547
z-stat	2.608	3.608	2.152
Implied r_f	-0.258%	-0.430%	-0.103%
Observations	3010	3010	3010

4 Out-of-Sample Tests

Strong results should be sustained across periods (Schwert (1990)). To check the out-of-sample robustness of our results, we rerun all tests on a new sample period from 2016 to 2018. Panel A of Table 11 shows the results of a precisely identified GMM test of the Euler equation for the excess market return; panel B provides an additional moment restriction of the risk-free rate; and panel C reports the results with the instruments.

We find that the relative risk aversion coefficient using out-of-sample data is 17.954, which is significant at the 1% level, compared with the coefficient of 9.217 using in-sample data. Including an additional moment decreases the risk aversion coefficient to 5.925 (compared to 5.159 in Table 4), whereas including the instruments results in a risk aversion coefficient of 11.957 (compared to 5.410 in Table 4). Table 11 also shows the implied risk-free rates: -0.32% in panel A and -0.11% in panel C (compared to -0.091% and 0.003% from Table 4). The insignificant p-values of the J-test in panels B and C indicate that they are adequately identified models. Table 11 is consistent with Table 4: the daily consumption measure delivers a low-risk aversion coefficient and implied risk-free rate.

Then we examine the cross-sectional implication of the model by rerunning the Fama and Macbeth (1973) regression with out-of-sample data. Panels A, B, and C of Table 12 report the price of consumption risk using 31 portfolios, 35 portfolios, and individual stocks, respectively.

We find that with 31 portfolios, λ_c is 0.715% compared with 1.289% in Table 5. With 35 portfolios, we observe λ_c of 0.553% versus 1.668% with in-sample data. With individual stocks as testing assets, λ_c decreases from 0.458% in Table 6 to 0.236% in Table 12. Meanwhile, all λ_cs are significant across all panels at either the 10% or 1% level. We conclude that the daily consumption-based model fits the cross-section of stock returns with the most recent data.

Table 11: Out-of-Sample Test: GMM Test and Risk Aversion Estimates

This table reports the GMM test results for the out-of-sample test of daily consumption growth from 2016 to 2018. Panel A shows the relative risk aversion (RRA) from the GMM test that uses the exactly identified model. The moment restriction is as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1}] = 0.$$

Panel B reports the results from a one-stage GMM with empirically observed risk-free rates. The moment restrictions are as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1}] = 0, \qquad E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^f_{t+1}] = 1.$$

Moreover, panel C shows the GMM test for estimating the RRA coefficient with instruments. The instrument set Z_t contains a constant, lagged consumption growth, one plus the lagged excess market return, and the detrended lagged log-price-to-dividend ratio. The moment restrictions are as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1} \otimes Z_t] = 0.$$

We fix β to be 0.95. R^e_{t+1} is the value-weighted CRSP index return over the daily risk-free rate. γ is the relative risk aversion, and we report its standard error, *z-statistics*, and mean absolute error (MAE). The implied risk-free rates are derived from RRA in panels A and C. The p-values are based on the J-test of over-identification conditions.

	Δc_t from 2016 to 2018
	Panel A. Equity Premium (Exactly Identified)
RRA (γ)	17.954
(s.e.)	6.808
z-stat	2.637
MAE	0.562
Implied r_f (%)	-0.320
Observations	753
	Panel B. Equity Premium and Risk-Free Rate (One-Stage GMM)
RRA (γ)	5.925
(s.e.)	0.378
z-stat	15.683
MAE	0.431
J-test *p-value*	0.695
Observations	753
	Panel C. Equity Premium and Instruments (One-Stage GMM)
RRA (γ)	11.957
(s.e.)	7.121
z-stat	1.679
MAE	0.562
Implied r_f (%)	-0.110
J-test *p-value*	0.450
Observations	752

Table 12: Out-of-Sample Test: Fama-MacBeth Cross-sectional Regressions

This table reports the prices of risk from the Fama-MacBeth two-path cross-sectional regressions for out-of-sample tests using the data period from 2016 to 2018. Δc_t denotes daily consumption growth. Panel A presents the results of the 31 portfolios as testing assets, including ten size-sorted, ten book-to-market-sorted, ten investment-sorted portfolios, and one market portfolio. Panel B presents the 35 portfolios as testing assets, including the 25 size- and book-to-market-sorted and ten industry portfolios. Panel C presents individual stocks as testing assets selected by the same screening criteria as Gu et al. (2020). Betas for each day are estimated using daily returns data over the previous year, and cross-sectional regressions are fitted using the IV and OLS methods. The regression includes a log of market cap and book-to-market ratio to control for firms' characteristics. For all models, we report six-lag Newey-West t-statistics in brackets. We also report the mean absolute pricing error (MAPE). *p <0.1; **p <0.05; ***p <0.01.

	Panel A. 31 Portfolios	*Panel B. 35 Portfolios*	*Panel C. Individual Stocks*
	(1)	(2)	(3)
Δc_t	0.715*	0.553*	0.236***
	(0.417)	(0.332)	(0.087)
log(Market Value of Equity)			0.000
			(0.000)
Book to Market Ratio			-0.000
			(0.000)
Constant	0.001	0.054*	0.073***
	(0.024)	(0.030)	(0.009)
Observations	23,343	26,355	1,414,515
R^2	0.132	0.136	0.040
MAPE	0.043	0.023	0.137

5 Applications

5.1 Hedging consumption risk

We endeavor to design a consumption risk hedging portfolio that effectively counteracts exposure to consumption risk while generating excess returns. This is achieved by constructing a portfolio that explicitly hedges consumption risk (henceforth, CR_t) or the risk associated with fluctuations in consumption. To execute this hedging strategy, we thoroughly explore the stocks that increase and decrease in value during the materialization of consumption risk.

We adopt the approach of Engle et al. (2020) to create the consumption risk hedging portfolio. Specifically, we project their daily consumption growth data onto firm-level characteristics, including firm-specific consumption risk exposure, book-to-market ratio, size, market excess return, and firm stock returns. Estimating firm-level consumption risk exposure is facilitated by the availability of unique data that assess firms' daily consumption growth. We leverage the GS1 Company Database (GEPIR) to link the products recorded in CPD to the firms via UPC barcodes. The ultimate parents' name for UPC barcodes is obtained through GEPIR, the sole U.S. vendor that provides this information. By aggregating all the products' sales at the firm-day level, we generate firm-level daily consumption growth, defined as the total sales of firm i consumed by all households in CPD on day t. The Nielsen data are unique in revealing sales growth at this high frequency; thus, it is a good instrument for developing the consumption risk hedging portfolio.[36] We then aggregate all product sales at the firm-day level and thus generate firm-level daily consumption growth, defined as the total sales of firm i consumed by all households in CPD on day t. Notably, the Nielsen data are the only data to reveal sales growth at this high frequency.

We then obtain firm-level risk exposure to consumption shocks by regressing the daily stock returns of firm i on the firm-level daily consumption growth. The consumption beta is computed for each month as follows:

$$R_{it} = \alpha + \beta_{\Delta c_{it}} \times \Delta c_{i_t}, \tag{25}$$

where $\beta_{\Delta c_{it}}$ captures the sensitivity of stock returns to consumption growth. The higher the $\beta_{\Delta c_{it}}$, the higher the sensitivity to consumption growth that firm i has. We define this beta exposure as firm-level consumption risk. To be consistent with Engle et al. (2020), we use one minus $\beta_{\Delta c_{it}}$ to represent low consumption risk, which we denote as $Z_t^{low-cons-risk}$. The higher the $Z_t^{low-cons-risk}$, the lower the consumption risk. In other words, firms with high consumption risk have stock returns that are more sensitive to consumption change.

To ensure cross-sectional standardization, each variable is assigned a mean of zero and a standard deviation of one for all sample firms per day, according to Fama and French (2020) and Engle et al. (2020).[37] The portfolio returns can be written as

$$\tilde{r}_t = Z'_{t-1} r_t, \tag{26}$$

where r_t denotes the excess returns of individual stocks, and Z_t denotes the firm-level characteristics. We consider these portfolios to be the sum of the monthly weighted returns of each firm based on the consumption beta, B/M, size, and market, respectively.

Next, we examine which firms provide high returns during high uncertainty. We relate high

[36] PERMNO is a unique permanent security identification number assigned by CRSP to each security.

[37] The results remain qualitatively the same if we standardize all the characteristics cross-sectionally by month.

economic uncertainty to consumption growth and define a high economic uncertainty period as when consumption growth (Δc_t) is low or stagnant. We define consumption risk (hereafter, CR_t) as one minus consumption growth (Δc_{it}) aggregated across firms. The lower the Δc_t, the higher the CR_t. We want to emphasize that $\beta_{\Delta c_{it}}$ from Equation (25) represents *firm-level* consumption risk exposure, whereas $1 - \Delta c_t$ or CR_t represents *aggregate* consumption risk exposure.

We project the aggregate consumption risk (CR_t) onto the firm-level characteristics portfolios.

$$\begin{aligned} CR_t =& 1 - \Delta c_t \\ =& \xi + w_{i,low-cons-risk}\tilde{r}_{i,t} \\ =& \xi + w_{i,low-cons-risk}Z_{i,t-1}^{low-cons-risk'}r_{i,t} \\ &+ w_{i,size}Z_{i,t-1}^{size'}r_{i,t} + w_{i,BM}Z_{i,t-1}^{BM'}r_{i,t} + w_{MKT}Z_{i,t-1}^{MKT}r_{i,t} + e_{i,t}, \end{aligned} \tag{27}$$

where $w_{i,low-cons-risk}$, $w_{i,size}$, $w_{i,BM}$, and $w_{i,MKT}$ are scalars that capture the weight of the corresponding portfolios in the consumption hedge portfolio. We estimate these weights and report the results in panel A of Table 13. We find that $\hat{w}_{low-cons-risk}$ is positive and significant, implying that a portfolio that longs stocks with low consumption risk and shorts the opposite during the high risk of consumption generates higher excess returns. An R^2 of 8% indicates portfolios based on our firm-level consumption risk can hedge 8% of the in-sample variation in the aggregate market consumption risk.

To illustrate an example, we use 2016, the first year of our out-of-sample period. We first rank the industries from highest to lowest portfolio weights in 2016. Next, we obtain the coefficients from Equation (27) using the CR_t and r_t data from 2004 to 2016 and Z_t data from 2004 to 2015 to estimate the portfolio weights in 2016. We then determine the firm's portfolio weight in 2016 using the following formula:

$$\hat{w}_{low-cons-risk}Z_{2015}^{low-cons-risk'} + \hat{w}_{size}Z_{2015}^{size'} + \hat{w}_{BM}Z_{2015}^{BM'} + \hat{w}_{MKT}Z_{2015}^{MKT'} + e_t. \tag{28}$$

The weight of each firm i in a portfolio depends on the beta exposure to consumption growth, firm size, and firm book-to-market. Ultimately, we combine the firms' weights within their respective industries and present the ranked industry weights in Panel B of Table 13. Our results suggest that investors should consider taking long positions in industrial and commercial machinery and computer equipment firms as a hedge against consumption risk while concurrently reducing their exposure to food and beverage stocks. Industrial and commercial machinery and computer equipment consumption typically require consumers to have a certain income level due to higher prices than other products. Consequently, the consumption of these items may serve as a reliable indicator of a robust economy and low consumption risk. In contrast, spending on food and related products is associated with low consumption growth (high consumption risk) since they are considered necessities with considerably lower prices.

Table 13: Hedging Consumption Risk

This table reports results from hedging consumption risk tests. We first link each product at the UPC level to public manufacturing firms with data in CRSP. Then we calculate a household consumption growth rate at each firm level based on its products' daily sales. We then regress each firm's daily stock return on such daily household consumption growth (Δc_t) and collect the beta specific to each firm for each month. We then transform the lagged one minus consumption beta, book-to-market ratio, size, and market excess return to z-score and denote them as $Z^{low-cons-risk}$, Z^{BM}, Z^{size}, and Z^{MKT}, respectively. We then multiply these Z-scores with contemporaneous firm return (r_t). Next, we regress the economy consumption risk (CR_t) on these four products (see the equation below). CR_t is a market-level consumption risk measure identifying market stagnancy. The higher CR_t, the more stagnancy and lower the market's consumption growth. See Section 5.1 for a detailed description. There are 143 observations based on the sample period from 2004 to 2015. We lost one month due to the computation of consumption growth. See Section 5.1 for a detailed description. Panel A shows the estimated coefficients or $w_{low-cons-risk}$, w_{size}, w_{bm}, and w_{MKT} from the following equation:

$$CR_t = \xi + w_{low-cons-risk} Z_{t-1}^{low-cons-risk'} r_t + w_{size} Z_{t-1}^{size'} r_t + w_{bm} Z_{t-1}^{BM'} r_t + w_{MKT} Z_{t-1}^{MKT} r_t + e_t.$$

Panel B presents the aggregate weight of $w_{low-cons-risk}$ at the industry level in 2016 as follows:

$$\hat{w}_{low-cons-risk} Z_{2015}^{low-cons-risk'} + \hat{w}_{size} Z_{2015}^{size'} + \hat{w}_{HML} Z_{2015}^{BM'} + \hat{w}_{MKT} Z_{2015}^{MKT'} + e_t.$$

Panel A. Regressing Aggregate Consumption Growth on Firm-Specific Characteristics and Returns

	CR_t
$Z_{t-1}^{low-cons-risk'} r_t$	0.043***
	(0.016)
$Z_{t-1}^{BM'} r_t$	0.039
	(0.031)
$Z_{t-1}^{Size'} r_t$	-0.002
	(0.039)
$Z_{t-1}^{Market'} r_t$	-0.046
	(0.032)
Observations	143
R^2	0.079
F-statistics	2.965

Panel B. Industry's Weights based on Firm Individual Consumption Hedging Portfolio Weights

Sic 2 Code	Industry
	Positive Weights
35	Industrial and Commercial Machinery and Computer Equipment
36	Electronic & Other Electrical Equipment & Components
23	Apparel, Finished Products from Fabrics & Similar Materials
73	Business Services
31	Leather and Leather Products
39	Miscellaneous Manufacturing Industries
48	Communications
32	Stone, Clay, Glass, and Concrete Products
45	Transportation by Air
50	Wholesale Trade - Durable Goods
33	Primary Metal Industries
59	Miscellaneous Retail
22	Textile Mill Products
27	Printing, Publishing, and Allied Industries
37	Transportation Equipment
99	Nonclassifiable Establishments
1	Agricultural Production - Crops
56	Apparel and Accessory Stores
13	Oil and Gas Extraction
24	Lumber and Wood Products, Except Furniture
30	Rubber and Miscellaneous Plastic Products
78	Motion Pictures
58	Eating and Drinking Places
79	Amusement and Recreation Services
49	Electric, Gas and Sanitary Services
14	Mining and Quarrying of Nonmetallic Minerals, Except Fuels
34	Fabricated Metal Products
25	Furniture and Fixtures
	Negative Weights
82	Educational Services
72	Personal Services
63	Insurance Carriers
60	Depository Institutions
29	Petroleum Refining and Related Industries
2	Agricultural Production - Livestock and Animal Specialties
67	Holding and Other Investment Offices
42	Motor Freight Transportation
51	Wholesale Trade - Nondurable Goods
54	Food Stores
65	Real Estate
26	Paper and Allied Products
55	Automotive Dealers and Gasoline Service Stations
21	Tobacco Products
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks
28	Chemicals and Allied Products
53	General Merchandise Stores
20	Food and Kindred Products

5.2 Tradable consumption factor

To ensure the robustness of our findings, we have constructed a consumption-mimicking portfolio (CMP), as outlined in Section 2.4, and have made it available on our website. In this section, we present the performance of the CMP at the daily level, focusing on assessing its effectiveness in an in-sample context.

We follow the same CMP approach used in Section 2.4 by projecting the daily consumption growth on a set of assets based on equation (23). But we limit our analysis to the sample period from 2004 to 2015 to fit an in-sample tradable consumption factor. To evaluate the performance of the CMP, we employ GMM and cross-sectional tests. We use the same excess market return for the GMM test to ensure consistency across our analyses. We consider various testing assets for the cross-sectional tests, including 35 portfolios comprising 25 size and book-to-market sorted portfolios and ten industry portfolios. We also examine 31 portfolios of 10 sizes, 10 book-to-market, ten investment growth sorted, and one market portfolio, individual stocks, and q-portfolios.[38] For individual stocks, we apply Jegadeesh et al. (2019)'s approach as explained in Section 2.3.

Panel A of Table 14 reports the GMM test. The in-sample daily CMP yields a risk aversion coefficient of 4.142, lower than the raw daily CG. We attribute this superior performance to the composition of the CMP, which includes assets that move closely with the market and the in-sample property of the CMP that retains the rich information of the raw daily CG. The implied risk-free rate is 0.023%, which is very close to the observed risk-free real-time rate.

Panel B of Table 14 shows the cross-sectional tests in the Fama-MacBeth framework. We find that the in-sample daily CMP carries a significantly positive risk premium in almost all specifications that control for either a market factor or Fama-French five factors plus a momentum factor.

Overall, this section shows that the traded version of in-sample daily consumption growth performs as well as the raw daily CG in both GMM and cross-sectional tests.

[38]q-portfolios are double-sorted portfolios based on size and characteristics from Lu Zhang's q-factor model data library, which results in over 2,800 portfolios.

Table 14: Factor-mimicking Portfolio and Asset Pricing Tests

This table reports the results of the traded version of our daily consumption Δc_t from applying the factor-mimicking portfolio (FMP) approach. Panel A reports the relative risk aversion (RRA) based on an identified GMM model. Panel B reports the prices of risk from the second step of the two-pass regression. We show the six factors from Fama and French (2018). Our testing assets include the following: (1) 31 portfolios consisting of 10 sizes, ten book-to-market, ten investment growth sorted, and one market portfolio; (2) 35 portfolios that comprise 25 size and book-to-market sorted portfolios and ten industry portfolios; (3) 6 size-BM, momentum sorted, and four bond portfolios, which are the base assets that we use to construct our CMP; (4) individual stocks where betas for each day are estimated using daily returns data over the previous one year and cross-sectional regressions are fitted using the IV and OLS methods; (5) q-portfolios. In Panel B, we report nine-lag Newey-West t-statistics for all models. *p <0.1; **p <0.05; ***p <0.01.

Panel A: CMP GMM Tests		*Panel B: FMB Tests*										
			31 Portfolios		35 Portfolios		6 Size-BM, MOM and 4 Bond Portfolios		Individual Stocks		Q Portfolios	
RRA	4.142		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(s.e.)	1.459	Daily CMP	0.583*	-0.003	0.724**	0.870**	0.142	1.351**	0.444***	0.27***	0.212***	0.171***
t stat	2.840		(0.343)	(0.005)	(0.329)	(0.394)	(0.307)	(0.608)	(0.092)	(0.065)	(0.021)	(0.011)
Implied r_f (%)	0.023	MRF	0.019	0.095*	0.015	-0.014	0.018	0.024	0.016	0.036**	0.024***	0.014***
			(0.027)	(0.054)	(0.028)	(0.068)	(0.019)	(0.018)	(0.011)	(0.012)	(0.000)	(0.000)
		SMB		0.009		0.011		0.015*		0.001		0.011***
				(0.011)		(0.014)		(0.009)		(0.005)		(0.000)
		HML		0.005		-0.002		0.002		-0.008*		0.000
				(0.022)		(0.024)		(0.011)		(0.005)		(0.000)
		RMW		0.010		0.010		0.093***		0.005*		-0.000*
				(0.014)		(0.013)		(0.033)		(0.002)		(0.000)
		CMA		-0.001		0.009		-0.063***		-0.005*		0.000***
				(0.008)		(0.012)		(0.022)		(0.005)		(0.000)
		UMD		0.057		0.077*		0.003		0.068***		0.000
				(0.039)		(0.043)		(0.021)		(0.009)		(0.000)
		Ln (Market Cap)							-0.001*	-0.002***		
									(0.001)	(0.001)		
		Book to Market							-0.000***	-0.000***		
									(0.000)	(0.000)		
		Constant	0.016	-0.045	0.023	0.030	0.013***	0.008*	0.016**	0.014	0.007***	0.011***
			(0.022)	(0.031)	(0.020)	(0.034)	(0.005)	(0.005)	(0.010)	(0.008)	(0.000)	(0.000)
		Observations	93,651	93,651	105,735	105,735	33,231	33,231	11,096,417	11,096,417	8,427,221	8,427,221
		R^2	0.310	0.672	0.316	0.657	0.670	0.957	0.021	0.037	0.022	0.035
		MAPE	0.018	0.002	0.010	0.008	0.008	0.007	0.009	0.012	0.011	0.004

6 Additional Robustness Tests

6.1 Decomposition of daily consumption growth

In light of potential concerns about the influence of seasonal trends on consumption growth and our findings, we undertake a decomposition analysis to isolate the weekly seasonality effect from the daily consumption series. This analysis aims to ensure that our baseline tests, which include GMM and a Fama-MacBeth cross-sectional regression, are robust and not influenced by any seasonal trends.

The results of our analysis are presented in Table 15, where we report the findings of our

GMM and cross-sectional regression tests. Panel A of Table 15 demonstrates that the model with precisely identified instruments yields a risk aversion estimate of 11.133, slightly higher than the estimate obtained from raw consumption growth (9.217). Including the observed risk-free rate reduces the risk aversion estimate to 3.65, representing a marked improvement compared to the estimate for raw consumption growth (11.133). Moreover, using instruments reduces the risk aversion estimate, albeit insignificantly, as evidenced by the standard error of 30.426.

Panel B of Table 15 shows deseasonalized consumption growth risk premiums against various testing assets. The λ_c are consistently significant at the 5% to 10% levels, indicating that daily consumption growth still carries a risk premium using any assets after removing seasonality.

Table 15 shows that the seasonality effect does not affect our results. Furthermore, we also run the analysis using only idiosyncratic components after excluding both the seasonality and trend components, and the results remain qualitatively the same. We do not report the results here for brevity, but they are available on request.

Table 15: Decomposition Tests

This table reports the GMM and the price of risk from the Fama-MacBeth two-pass cross-sectional regression results of the deseasonalized daily consumption series. We first decompose the daily consumption growth (Δc_t) to isolate the seasonality component. We use the deseasonalized consumption series to run GMM and report the Relative Risk Aversion (RRA) in panel A. In addition, we also calculate the risk premium based on Fama-MacBeth two-path cross-sectional tests in panel B. Our testing assets include (1) 31 portfolios consisting of 10 sizes, ten book-to-market, ten investment growth sorted, and one market portfolio; (2) 35 portfolios that comprise 25 size and book-to-market sorted portfolios and ten industry portfolios; (4) q-portfolios; (5) individual stocks. t stats are reported in the brackets. For all models, we report nine-lag Newey-West t-statistics. *p <0.1; **p <0.05; ***p <0.01.

Panel A: GMM	CG-Seasonaility	Panel B: Fama-MacBeth	*31 Portfolios*	*35 Portfolios*	*Q Portfolios*	*Individual Stocks*
	Equity Premium (Exactly Identified)					
RRA (γ)	11.133	CG-Seasonaility	0.390*	0.579**	0.477*	0.172*
(s.e.)	3.173		(0.216)	(0.265)	(0.275)	(0.130)
t stat	3.509					
MAE	0.016	Log(Market Value of Equity)				-0.117
Implied r_f	-18.000%					(0.078)
	Equity Premium and Risk-free Rate (One-stage GMM)					
RRA (γ)	3.653	Book to Market Ratio				0.818***
(s.e.)	0.228					(0.081)
t stat	16.016					
MAE	0.027	Constant	0.044**	0.046**	0.038**	0.026*
J-test *p-value*	0.082		(0.018)	(0.018)	(0.019)	(0.021)
	Equity Premium and Instruments (One-stage GMM)					
RRA (γ)	1.144					
(s.e.)	30.426					
t stat	0.038					
MAE	0.0028	Observations	92,101	103,985	8,287,771	10,814,041
Implied r_f	0.053%	R^2	0.192	0.173	0.175	0.069
J-test *p-value*	0.157	MAPE	0.036	0.037	0.04	0.022

6.2 Expenditure-sorted consumption growth

In testing the relationship between household expenditures and their risk aversion estimates, we confront the challenge of unavailable household wealth information. As Ait-Sahalia et al. (2004) suggest, households allocating a larger share of their wealth to consumption expenditures should exhibit lower risk aversion than those spending less on consumption. To circumvent this challenge, we rely on the assumption that households with greater wealth tend to have higher total expenditures. Specifically, we sort households' daily total expenditures into top and bottom deciles, above- and below-median expenditures, respectively, and subsequently estimate risk aversion separately for each group.

The results of our analysis, as presented in Table 16, support the conjecture that households with greater wealth exhibit lower risk aversion than their less affluent counterparts. In Panel A, we report the risk aversion estimates obtained through a precisely identified GMM model. The risk aversion estimates for the top decile or above-median groups are consistently lower than those for the bottom decile or below-median groups, implying that relatively affluent households are less averse to risk and better able to strike an optimal balance between consumption and investment. This finding is robust to alternative specifications, as demonstrated in panels B and C of Table 16.

6.3 Weekly consumption growth

Having verified that daily consumption growth can generate a moderate risk aversion estimator and price returns at the cross-section, we now check whether the results hold using weekly data. Household consumption happens daily; thus, the daily measure is the suitable horizon, confirmed by the pattern we observe in CPD. However, we allude to the weekly measure to address the possible heterogeneity across the leisure constraint.

We compute weekly consumption growth from the first day to the last consumption day for a week.[39,40] First, we present the summary statistics in Table 17. Column 2 reports the summary

[39]Weekend consumption is very likely different from weekday consumption. For example, during weekdays, households can be constrained by their working hours, whereas during weekends, households likely have more hours available for consumption.

[40]Our first weekly consumption growth observation is January 7, 2004. For the first weekly observation, the first day (January 1, 2004) is Thursday, and the seventh (January 7, 2004) is Wednesday.

Table 16: Expenditure-sorted Consumption Measures and GMM Tests

In this table, we sort total expenditure per trip per day into the top and bottom deciles and above- and below-median groups. Then we calculate each group's daily consumption and run GMM tests using the same methodology and models in Table 4. The p-values are based on the J-test of over-identification conditions. Similar to Table 4, we report RRA, implied risk-free rate, and MAE.

	Top Decile Consumption	Bottom Decile Consumption	Above-median Consumption	Below-median Consumption
Panel A. Equity Premium (Exactly Identified)				
RRA (γ)	8.006	13.317	9.078	12.023
(s.e.)	2.443	8.873	2.922	7.188
t-stat	3.276	1.501	3.107	1.673
MAE	0.344	0.743	0.424	0.693
Implied r_f (%)	-0.090	-0.220	-0.110	-0.190
Panel B. Equity Premium and Risk-free Rate (One-stage GMM)				
	Top Decile Consumption	Bottom Decile Consumption	Above-median Consumption	Below-median Consumption
RRA (γ)	4.567	5.728	5.081	5.578
(s.e.)	0.179	0.178	0.188	0.176
t-stat	25.514	32.180	27.027	31.693
MAE	0.330	0.732	0.413	0.683
J-test p-value	0.214	0.217	0.224	0.280
Panel C. Equity Premium and Instruments (One-stage GMM)				
	Top Decile Consumption	Bottom Decile Consumption	Above-median Consumption	Below-median Consumption
RRA (γ)	4.538	9.033	5.236	7.840
(s.e.)	2.089	7.063	2.388	5.729
t-stat	2.172	1.279	2.192	1.368
MAE	0.449	0.872	0.516	0.769
Implied r_f (%)	0.020	-0.080	0.010	-0.060
J-test p-value	0.519	0.463	0.571	0.498

statistics for weekly consumption growth. To facilitate comparison, we report the summary statistics again for daily consumption growth and the existing annual consumption measures. A key observation is that with a standard deviation of 4.583%, weekly consumption growth is one and a half times more volatile than garbage growth, whose standard deviation is 2.973%. However, as expected, the standard deviation of weekly consumption growth is lower than that of daily consumption growth.

Table 18 shows the results of a GMM test of the Euler equation for the excess market return. For comparison, we also report those risk aversion estimators derived from daily consumption and other annual measures. Weekly consumption growth generates a significant risk aversion estimate

Table 17: Summary Statistics

In this table, panel A presents the summary statistics of weekly consumption growth (Weekly Δc_t). We report the mean, standard deviation, and variance, in addition to the autocorrelation and the correlation with the market return. For comparison, we also report the same statistics for daily consumption growth and other consumption measures in the same sample period as our weekly measure. We report the statistics for the other consumption measures in the full sample period in panel B. Δc_t, garbage, unfiltered NIPA, P-J Dec-Dec, and Q4-Q4 are the consumption growth based on our daily consumption growth, Savov (2011), Kroencke (2017), Parker and Julliard (2005), and Jagannathan and Wang (2007), respectively collected from Professor Kroencke's website. *Garbage data are available from 1960 to 2007.

	Panel A. Sample Period (2004-2015)					*Panel B. Sample Period (1960-2014)*			
	Weekly Δc_t	Δc_t	Unfiltered NIPA	P-J Dec-Dec	Q4-Q4	Garbage*	Unfiltered NIPA	P-J Dec-Dec	Q4-Q4
Mean (%)	-2.418	0.170	1.054	2.723	0.932	1.472	1.513	2.118	1.518
Standard Deviation (%)	4.583	6.164	2.199	2.810	1.252	2.973	2.618	1.385	1.980
Variance (%)	0.210	0.380	0.048	0.079	0.016	0.088	0.069	0.019	0.039
Autocorrelation (1) (%)	1.108	-19.410	31.210	66.950	50.250	-14.510	-8.310	80.180	21.790
Correlation with Rm (%)	1.316	2.640	73.509	59.384	69.542	19.705	33.432	39.569	39.699
Covariance with Rm (%)	0.001	0.185	0.292	0.301	0.157	0.095	0.139	0.087	0.125

of 13.028, smaller than the RRA generated from other measures. It is almost five times smaller than that of Q4-Q4. On the other hand, a risk aversion estimate of 13.028 is larger than the risk aversion estimate derived from our daily consumption measure, consistent with our argument: low-frequency aggregate consumption growth performs worse than higher-frequency consumption growth. Daily frequency has the highest covariance with excess returns and, thus, the lowest risk aversion. The higher the frequency of our consumption, the better the performance. The implied risk-free rate from the weekly consumption growth is -66.571%, which is consistent with the negative implied risk-free rate derived from daily consumption growth.[41]

Then we check whether weekly consumption growth can help us understand the observed cross-sectional variation in the average returns. Table 19 presents the price of risk from the second step Fama-MacBeth regressions, with portfolios as testing assets. We employ the conventional testing assets using 31 and 35 portfolios in panels A and B, respectively. With 31 portfolios across different model specifications, we do not find significant coefficients for weekly consumption growth. With 35 portfolios, weekly consumption growth used as the sole factor obtains a positive and considerable premium of 1.1%. Including the market factor, weekly consumption growth remains a significant premium of 1.3%. When we include SMB and HML, the premium associated with the weekly consumption growth is lost in magnitude and significance. We also observe this

[41]We need to be cautious when comparing this weekly risk-free rate with other annual risk-free rates derived from yearly consumption. The weekly risk-free rate should not be directly annualized. To calculate the yearly risk-free rate, we should use annual frequency CG. Data limitations, however, preclude us from doing so.

Table 18: GMM Test and Risk Aversion Estimates of Weekly Consumption Growth

This table shows the GMM test on estimating the relative risk aversion coefficient with different consumption measures from 2004 to 2014. Weekly Δc_t denotes our weekly consumption growth. The model in this table uses the exactly identified model. The moment restriction is as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma} R^e_{t+1}] = 0,$$

where β is set to 0.95. R^e_{t+1} is the value-weighted CRSP index return over the daily risk-free rate, and γ is the relative risk aversion (RRA). We also report RRA's standard error. The implied risk-free rate (r_f) is derived from RRA. Δc_t, Garbage, unfiltered NIPA, P-J Dec-Dec, and Q4-Q4 are the consumption growth based on our daily consumption growth, Savov (2011), Kroencke (2017), Parker and Julliard (2005), and Jagannathan and Wang (2007), respectively collected from Professor Kroencke's website.

	Weekly Δc_t	Daily Δc_t	Annual Garbage (1960-2007)	Annual Unfiltered NIPA (1960-2014)	P-J Dec-Dec (1960-2014)	Q4-Q4 (1960-2014)
RRA (γ)	13.028	9.217	15.630	22.530	42.350	64.050
(s.e.)	2.429	3.030	8.380	11.980	22.870	39.610
$z\text{-}stat$	5.364	3.042	1.865	1.881	1.852	1.617
Implied r_f (%)	-66.571	-0.091	17.250	30.090	158.190	82.600
Observations	626	3021				

with the garbage data.

Panel C reports the results with 120 double-sorted portfolios randomly selected from Lu Zhang's library. Unlike other low-frequency consumption measures in the literature, our high-frequency consumption measures have a lot of time-series observations T, enabling us to conduct a Fama-MacBeth test with many testing assets. We choose 120 portfolios consistent with a similar T/N ratio from Kleibergen and Zhan (2020). We find that the price of consumption risk is 8.9% and significant, including the market factor. Paired with three-FF factors, the consumption factor price jumps to 13.0%.

Table 19: Fama-MacBeth Cross-sectional Regressions:
***Weekly* Consumption Growth and Portfolios as Testing Assets**

This table reports the prices of risk from the Fama-MacBeth two-pass cross-sectional regression of Fama and French (2018)'s five factors. Weekly Δc_t denotes our weekly consumption growth. Panel A presents the testing assets of 31 portfolios, including ten size, ten book-to-market, and ten investment-sorted portfolios, in addition to 1 market portfolio. Panel B presents the testing assets of 35 portfolios, including 25 sorted by size and book-to-market and ten industry portfolios. Panel C uses 120 randomly selected double-sorted portfolios from Lu Zhang's library. We report six-lag Newey-West t-statistic in brackets and report mean absolute pricing error (MAPE) for all models. *p <0.1; **p <0.05; ***p <0.01.

Panel A. 31 Portfolios

	(1)	(2)	(3)	(4)	(5)
Weekly Δc_t	0.004	0.004	-0.001	0.001	0.003
	(0.007)	(0.006)	(0.005)	(0.005)	(0.004)
MRF		-0.000	0.000	0.001	0.001
		(0.002)	(0.001)	(0.001)	(0.001)
SMB			0.000	0.000	0.000
			(0.001)	(0.001)	(0.001)
HML			-0.000	-0.000	-0.000
			(0.001)	(0.001)	(0.001)
CMA				0.000	0.000
				(0.000)	(0.000)
RMW				0.000	0.000
				(0.000)	(0.000)
UMD					0.002**
					(0.001)
Constant	1.002***	1.002***	1.001***	1.001***	1.000***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	21,910	21,910	21,910	21,910	21,910
R^2	0.137	0.332	0.552	0.642	0.687
MAPE	0.992	0.012	0.260	0.187	0.170

Panel B. 35 Portfolios

	(1)	(2)	(3)	(4)	(5)
Weekly Δc_t	0.011*	0.013**	0.001	-0.003	-0.005
	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)
MRF		-0.001	0.000	-0.000	0.000
		(0.002)	(0.001)	(0.001)	(0.001)
SMB			0.000	0.000	0.000
			(0.001)	(0.001)	(0.001)
HML			-0.000	-0.000	-0.000
			(0.001)	(0.001)	(0.001)
CMA				0.000	0.000
				(0.000)	(0.000)
RMW				0.000	0.000
				(0.000)	(0.000)
UMD					0.003
					(0.001)
Constant	1.002***	1.002***	1.002	1.002	1.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	21,910	21,910	21,910	21,910	21,910
R^2	0.125	0.321	0.545	0.639	0.685
MAPE	0.990	0.042	0.441	0.407	0.393

Table 19: (Cont.)

	(1)	(2)	(3)	(4)	(5)
Panel C. 120 Portfolios					
Weekly Δc_t	0.031	0.089**	0.130**	0.049	0.082
	(0.027)	(0.043)	(0.054)	(0.055)	(0.057)
MRF		0.110***	0.150***	0.194***	0.223***
		(0.006)	(0.007)	(0.007)	(0.009)
SMB			0.005***	0.007***	0.009***
			(0.001)	(0.002)	(0.002)
HML			0.016***	0.019***	0.030***
			(0.003)	(0.004)	(0.004)
CMA				0.009***	0.006*
				(0.003)	(0.003)
RMW				0.006	-0.004
				(0.004)	(0.004)
UMD					0.046***
					(0.005)
Constant	0.982***	0.883***	0.850***	0.803***	0.777***
	(0.002)	(0.006)	(0.070)	(0.008)	(0.009)
Observations	74,966	74,966	74,966	74,966	74,966
R^2	0.025	0.134	0.171	0.228	0.259
MAPE	0.978	0.040	0.413	0.192	0.142

As explained before, one of the advantages of having a large number of time-series observations is to conduct FM regressions with a relatively large number of cross-sectional observations. Table 20 shows the results with individual stocks as testing assets using Jegadeesh et al. (2019)'s approach. Weekly consumption growth has a stable, positive premium. The magnitude and significance of the weekly consumption premium increase in the presence of MRF, Fama-French three factors, and Fama-French five factors plus UMD.

Table 20: Fama-MacBeth Cross-sectional Regressions:
***Weekly* Consumption Growth Individual Stocks as Testing Assets**

This table reports the prices of risk from the Fama-MacBeth two-pass cross-sectional regressions of Fama and French (2018) 's six factors. We use individual stocks as testing assets. Weekly Δc_t denotes our weekly consumption growth. We include each model's log-transformed market value of equity and book-to-market ratio to control individual stocks' characteristics. We report the six-lag Newey-West t-statistic in brackets and the mean absolute pricing error (MAPE). *p <0.1; **p <0.05; ***p <0.01.

	Individual Stocks				
	(1)	(2)	(3)	(4)	(5)
Weekly Δc_t	0.003	0.003***	0.002**	0.002**	
	(0.002)	(0.001)	(0.001)	(0.001)	
MRF		-0.000	-0.000	0.000	0.000
		(0.001)	(0.000)	(0.000)	(0.000)
SMB			-0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)
HML			-0.000*	-0.000	-0.000
			(0.000)	(0.000)	(0.000)
CMA				-0.000	-0.000
				(0.000)	(0.000)
RMW				0.000	-0.000
				(0.000)	(0.000)
UMD				0.001***	0.002***
				(0.000)	(0.000)
log(Market Value of Equity)	-0.002**	-0.001	-0.003*	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Book to Market Ratio	0.000	0.001***	0.000***	0.000***	0.000***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.001***	1.001***	1.002***	1.001***	1.001***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11,116,267	11,056,111	11,115,895	11,115,255	11,110,692
R^2	0.009	0.021	0.031	0.042	0.039
MAPE	0.993	0.057	0.539	0.256	0.260

Tables 19 and 20 together are also consistent with Kleibergen and Zhan (2020)'s argument that there exists an optimal range for the number of testing assets (N) for a fixed number of time-series observations (T). When T increases, 31 or 35 portfolios could be less efficient for FM cross-sectional regressions.

Overall, this section results in three observations. First, weekly consumption growth, which is a relatively higher-frequency measure, can explain the equity premium puzzle with a smaller, relatively minor risk aversion estimator, performing better than the existing annual consumption growth measures. Second, utilizing high frequency, we conduct FM regressions with the 31/35 portfolios but also 120 characteristics-sorted portfolios and individual stocks. Weekly consumption performs well with many testing assets and explains the cross-sectional returns at least as well as garbage, with testing assets being 35 portfolios. Third, the performance of weekly consumption growth seems worse than that of daily consumption growth. This result is consistent with the underlying stochastic process of daily consumption growth. The model strongly indicates that aggregating high-frequency consumption growth to low-frequency consumption growth could result in much information being lost. Ignoring this information results in measured consumption that is too smooth and with a much higher level of relative risk aversion.

7 Conclusion

Our study employs daily consumption as the basis for reevaluating Euler equation within the standard consumption-based capital asset pricing model. Our results demonstrate that using daily consumption in the CCAPM produces an equity premium consistent with a relative risk aversion coefficient of 9.217. Furthermore, through joint pricing tests, we find a low-risk aversion coefficient of 5.159, indicating that daily consumption surpasses garbage and unfiltered NIPA measures to resolve the equity premium and risk-free rate puzzles. In addition, our daily consumption-based model explains the variation of stock returns cross-sectionally. We post the daily data of consumption growth mimicking portfolios on our website for researchers and practitioners to replicate and implement our applications. Our consumption-mimicking portfolio yields similar and consistent results with the original consumption growth data.

Besides showcasing the asset pricing performance of daily consumption Euler equations, our paper underscores the significance of short-term components and intra-annual dynamics in conditional high-frequency consumption volatility. Future research may fruitfully investigate whether incorporating an asymmetric correlation between short-term dynamics and low-frequency volatility or a fat-tailed distribution of daily consumption growth could improve the proxy for consumption volatility dynamics and bolster asset pricing implications. Additionally, it would be valuable to explore the implications of daily consumption measures for asset pricing models beyond CRRA preferences, which could yield novel insights into the valid properties of consumption growth.

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