

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. Through the decomposition of 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 Classification: C12, E21, E44, G12

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

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1 Introduction

Can consumption risk adequately explain the equity premium? The past dozen years have witnessed an explosion of studies striving to answer this critical question. The limited success of this classic model is attributed to the consumption measure, which has a low frequency and suffers from measurement errors. The failure of the CCAPM 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 This paper offers a novel solution that mitigates the reliance on such models by introducing a new measure of consumption that aligns with the CCAPM theory.

Our innovative consumption measure captures households' daily spending on all trips related to food and groceries, providing a real-time synchronization with asset returns. It offers a more accurate assessment of actual expenditures and provides a time stamp that is unavailable in other consumption measures. In particular, traditional measures represent consumption flows over discrete intervals, leading to time aggregation bias and measurement errors that arise from complex procedures used in their construction.²

In contrast, our data are pristine and not subject to complex procedures that cause time aggregation bias or measurement errors. By capturing households' daily spending on food and groceries, our measure provides a more precise reflection of consumption patterns, enabling a more accurate evaluation of the role of consumption risk in explaining the equity premium.

For spending to accurately reflect consumption, the products purchased must be consumed on the same day. Our data represent a reasonable approximation of consumption, as it primarily

¹It also leads to an explosive development of the characteristics-based asset pricing model, which falls under a debate of "factor zoo." Researchers have proposed over one hundred characteristics and four hundred factors, but determining the one that can explain expected returns or present risks is still questionable. 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 Restoy and Weil (2011), Bansal and Yaron (2004), and Bansal et al. (2012) (long-run risks); See Constantinides and Duffie (1996) (market incompleteness); and Mankiw and Zeldes (1991) (limited market participation). These models include more components to make the CCAPM work.

²Time aggregation bias refers to the distortion in data that arises when data is aggregated over time 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.

consists of nondurable goods, with only a small portion, less than ten percent, comprising relatively slow-to-consume goods, and none of them being typical durable goods (see Table 1 for the breakdown). Furthermore, to ensure that the spending data accurately represents consumption, we conducted 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 households' consumption, there is limited empirical evidence, primarily due to the absence of daily consumption statistics.³ 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, revealing a positive correlation between daily consumption and systematic risks. Additionally, we construct a weekly measure, with the findings demonstrating qualitative comparability to the daily measure.

We do not assert the superiority of our daily measure over other consumption measures, as direct comparisons are not feasible.⁴ Rather, our objective is to propose a high-frequency measure of consumption growth that can provide an adequate explanation for 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.

It is noteworthy that our cross-sectional asset pricing test is conducted on a daily frequency that aligns with the daily consumption growth. The use of a daily application provides certain advantages, as daily return prediction is more challenging than monthly return prediction. 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

³See Guiso and Haliassos (2001) for theoretical relationship between stock returns and consumption.

⁴The majority of 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 due to consumption estimates being 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 in Section 3.1. Thus, comparing aggregated consumption measures with other annual measures would yield a distorted evaluation of our daily measures.

to Cochrane, these factors are more likely to undergo change over long-term horizons than over short-term horizons, such as daily. That is to say, asset returns are more likely to be predictable over longer horizons. Given that daily asset return prediction is more challenging, it is essential to develop an asset pricing implication that accounts for daily frequency. Furthermore, the daily frequency allows for a more precise estimation of beta, which is prone to error-in-variable bias, as compared to monthly data.

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 heteroskedasticity (AR-spline-GARCH) model to our data. We show two components that characterize our measure. First is the time-series dynamics (short-term fluctuations), which are ignored in the annual consumption measure. Second is the slowly evolving macroeconomic effect (low-frequency volatility), which comprises intra-annual fluctuations and long-term trends.

The annual consumption measure is solely characterized by long-term trends, as opposed to intra-annual fluctuations and short-term dynamics. Low-frequency consumption loses most information during the aggregation and 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 post* 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 has high variability and contains both components.⁶ Liu and Matthies (2022) show the evidence supporting our premise in that about 80% of the pricing power of five alternative consumption measures comes from the

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

short-horizon component.

Initially, we observe that the daily consumption measure displays a remarkable ability to account for the observed equity premium, with a relative risk aversion (RRA) coefficient of 9.217, a much smaller figure compared to the coefficients of 15.63 and 22.53 for Garbage and unfiltered NIPA, respectively. This finding aligns with the arguments advanced by Mehra and Prescott (1985), who assert that a relative risk aversion parameter exceeding 10 is implausible. Notably, incorporating the instrument as a testing asset widens the gap further: the point estimate for the RRA coefficient for the daily consumption measure drops from 9.271 to 5.41, while the corresponding figures for Garbage and unfiltered NIPA are 16.96 and 15.38, respectively. Additionally, the daily consumption measure generates a considerably low risk-free rate ranging between 0.003% and -0.091% , compared to Garbage and unfiltered NIPA, which have average risk-free rates of 17.50% and 27.49%, respectively. 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. Thus, this outcome attests to the success of daily consumption measures in resolving the equity premium and risk-free rate puzzles. Our results remain robust even when applied out-of-sample from 2016 to 2018.

In the second part of our study, we evaluate the performance of the daily consumption-based model in explaining stock returns cross-sectionally. To this end, we utilize Jegadeesh et al. (2019)'s instrumental variable approach, where we utilize odd months to estimate beta using daily returns for the preceding three years on a rolling basis, while even months are used to estimate another beta for use as an instrument. This approach reduces error-in-variable bias during beta estimation and allows us to assess individual stocks more comprehensively, providing richer information than portfolios.⁷

The choice of testing assets can have an impact on the statistical significance of risk premiums, as highlighted by Lewellen et al. (2010). To ensure the robustness of our findings, we subject our results to a battery of tests involving a large and diverse set of assets, including 25 size and book-

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

⁷Jegadeesh et al. (2019) advocate for the utilization of individual assets as test assets, as opposed to 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, which allows for the capture of more detailed information regarding the assets' characteristics.

to-market portfolios by Fama and French (1996), 10 industry portfolios, 31 portfolios consisting of deciles sorted by size, value, and investment, as well as an additional equity premium portfolio, Feng et al. (2020) testing assets, and individual stocks. It is worth noting that, due to the limited frequency of their data, extant measures of consumption may not allow for such a wide range of testing assets. Our results corroborate Cochrane (2009) contention 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.

To facilitate a fair comparison with other consumption measures, we adopt a factor-mimicking portfolio approach to construct a tradable version of the daily consumption series extending back to 1960, which is 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 addition to our main findings, we are able to leverage the granularity of our data to 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 of 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 non-food grocery and general merchandise, the risk aversion coefficient is 9.698, aligning with our expectations. This outcome supports 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 for hedging consumption risk. In a similar vein to 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 simultaneously generating high excess returns. This is because the demand for industrial and commercial machinery and computer equipment will likely increase in parallel with rising consumer wealth and decreasing consumer risk.

We have conducted several tests to ensure our findings' robustness and validity. Firstly, we have created a consumption-mimicking portfolio (CMP) using daily frequency data within the same sample period, which produces an RRA of 4.142 and consistently generates a positive and significant risk premium across various testing assets. This portfolio serves as a replication for other researchers who wish to validate our results.⁸ Secondly, to address the potential issue of seasonality in our consumption growth data, we have decomposed it into a trend, seasonality, and idiosyncratic components. Upon removing the trend and seasonality, we observe similar qualitative results. Thirdly, our analysis reveals that the households that spend the most on consumption have the lowest risk aversion, which is consistent with the argument put forth by Ait-Sahalia et al. (2004). Lastly, we have repeated our tests using weekly consumption data to account for the weekend effect on daily consumption. We find that our weekly consumption growth measure continues to perform better than other existing measures in GMM tests and is a significant factor in the cross-section.

Related Literature. 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 to proxy 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)

⁸The dataset used in this study is accessible through the website <https://www.kuntara.net/>. Interested parties may contact the authors directly to request access to the data and corresponding replication codes. It should be noted that due to a copyright agreement with Nielsen, the data cannot be made available online.

and Kroencke (2017) address the shortcomings of NIPA consumption using filtered and unfiltered consumption, respectively. Liu and Matthies (2022) put forth a novel measure of consumption growth based on news. Their consumption measure is monthly while ours is daily. Their measure is based on the number of news articles with consumption-related keywords, whereas ours is based on grocery expenditures. They focus on demonstrating the existence of a persistent component in consumption growth, while ours is on explaining the equity premium puzzle. Both studies complement each other and confirm consumption growth can explain stock returns cross-sectionally.

Existing literature advocates for using an improved consumption measure in asset valuation. Our research builds upon this strand of literature by demonstrating that the CCAPM using a daily consumption measure matches the equity premium with a low relative risk aversion and implies a risk-free rate consistent with the actual interest rate. As a result, we provide a formal solution to the puzzle concerning the simultaneous equity premium and the risk-free rate.

This paper also relates to the extensive literature studying the underlying stochastic consumption growth process. Bansal et al. (2014) and Campbell (2018) argue that volatility shocks are priced, even conditional on those 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 returns' cross-section. However, Zviadadze (2021) argues that shocks to the consumption growth variance and the long-run volatility explain most of the time-series variation in the interest rate. Dew-Becker and Giglio (2016) argue that highly 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. 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

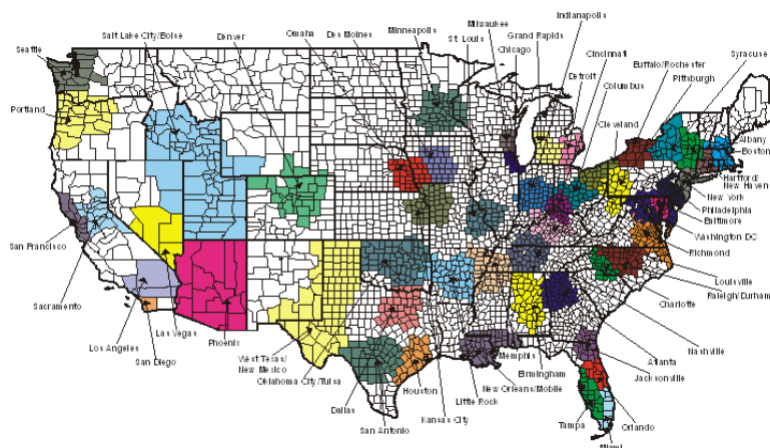
measure in explaining stock return variation at cross sections.

2 Data

We use the Consumer Panel Data (CPD) from the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business. The CPD is a panel of approximately 40,000 to 60,000 households geographically dispersed and demographically balanced across the United States. This dataset records the quantity and price of specific products households buy during a trip on a particular day. The markets covered by CPD consist of 52 Nielsen-defined Scantrack areas encompassing around 30% of household consumption in the US. Figure 1 shows the geographic markets that the CPD cover.

Figure 1: **Nielsen Market Penetration**

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



The purchased product is identified at the barcode level, a 12-digit universal product code (UPC) representing the most granular level of product identification. Each product has a unique barcode, and any change in product attributes will result in a new barcode.⁹ Panelists participating in the CPD program use in-home scanners to track all the products they purchase in one trip with information on prices and quantities. A trip could also be online, so households would follow the same process of scanning the products they purchase online. The scanner given to the panelists is similar to what is used in supermarkets. Hence, each observation unit is the price and

⁹One possible concern is that a new UPC might not always represent a new product. Nielsen assigns a new UPC to a product not recognized before, which does not mean that this product is new.

quantity of a particular product bought by a household during one specific trip in a day. The products include groceries, drugs, small appliances, and electronics.

Importantly, panelists also report their total expenditure on that particular trip and the spending only on grocery products tracked by a UPC. For a hypothetical example, suppose on one trip during a specific day, a household bought a gallon of milk for \$6 and computer software 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 software for two UPC barcodes but report \$86 as the total expenditure. Therefore, the 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 for which activity the \$50 is spent in this example.

To ensure data quality, Nielsen implements several methods. First, Nielsen validates the reported consumer spending with the scanner data of retailers quarterly. Second, Nielsen forms weekly sample reports to monitor whether there is any outlier. Lastly, Nielsen deletes households who do not report the required minimum consumption in the past 12 months and uses various incentives to retain panelists.¹⁰ Thus far, it has retained 80% participating households. Nielsen carefully designs incentives that do not cause any bias in shopping behavior. The incentives include 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, which cannot be tracked and are impossible to record at the household daily trip-product level.

The 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 characteristics, 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 the

¹⁰Nielsen's strategies include a monthly newsletter, telecommunication, gift point statement (see page 13 of their manual).

total daily spending based on the monthly inflation rate. We end up with 4,370 days with a total expenditure of 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. The excess market return is the daily CRSP equal-weighted index return minus the risk-free daily rate reported in Professor Ken French's data library. We merge our data with 25 Fama-French size and book-to-market portfolios and ten industry portfolios from Prof. Ken French's data library to conduct cross-sectional tests. 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 the consumption growth data of 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, from Professor Kroencke's website.¹²

We merge the daily consumption data with daily stock return data by excluding the weekends. However, since consumption during weekends contains the wealthiest 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 consumption measures in percentage. Panel A shows both measures daily 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

¹¹The projection factor represents the weight of each household relative to the US population. In other words, the sum of the weights (projection factors) is the total household population (i.e., the number of households) in the US. 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. Please consult with Nielsen at the Chicago Booth School of Business with further questions about their methodology and data collection.

¹²We thank Professor Kroencke for generously providing the data and codes to generate these data on his website, <https://sites.google.com/site/kroencketim/>

¹³When we compute stock returns on Monday as an opening to close and calculate the corresponding consumption growth on Monday with Monday's 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 reports the breakdown of household products consumed in our data and Panel D shows the summary statistics for household characteristics.

	<i>Panel A. Sample Period (2004-2015)</i>					<i>Panel B. Sample Period (1960-2014)</i>				
	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	
<i>Panel C. Product Breakdown</i>										
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										23.80%
Main Sample										100.00%
<i>Panel D. Household Characteristics</i>										
										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 the summary statistics from 1960 to 2007. In addition, we should summarize products consumed daily by the households in our sample.

Panel A of Table 1 shows that households spend around 0.17% more on the next day, which is 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 difference could come from the data frequency. The standard deviation of the daily consumption measure is 6.164%, indicating significant consumption volatility in our household samples. Theoretically, consumption volatility can be larger than stock returns volatility.¹⁴ Daily consumption shows a significantly negative autocorrelation, suggesting that households' current spending is negatively correlated with the past, and households might be cautious about their everyday spending.

We present an analysis of the annual consumption measure Δc_t derived from daily consumption data after adjusting for time-aggregation bias. Notably, the non-normal distribution of the daily consumption data precludes straightforward annualization of daily moments.¹⁵ Hence, caution is warranted when comparing the resulting annual Δc_t with other consumption measures. For

¹⁴We thank an anonymous associated editor for this comment.

example, the annual standard deviation can not be derived based on the daily standard deviation and the number of days. Our findings reveal that the annual Δc_t exhibits a 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 Eq (2), 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 resulting 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 Δc_t specifically designed to capture the strength of daily frequency data. Therefore, annual Δc_t may not accurately reflect the underlying strength of the 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 in financial and economic data analysis.

Panel C of Table 1 presents the breakdown of the daily products purchased by households in our sample. Our sample includes products that require immediate consumption, such as Magnet products, which constitute 19% of the sample and are often made-to-order or in-store baked. Furthermore, 58% of the products belong to fresh produce, dairy, or deli counters, while only 23% require a slower consumption rate. Panel D of Table 1 summarizes essential household characteristics, revealing that our sample comprises employed individuals in their early 50s, married, and having two to three members living in a single-family house.

Establishing a correlation between stock returns and daily consumption is crucial. It sheds light on the relationship between these two variables, which has not been explored in previous research due to the absence of daily expenditure data before introducing the Consumer Panel Data (CPD). In our study, we aim to fill this gap in the literature by investigating the relationship between daily stock returns and consumption. However, it is worth noting that the CPD does not provide information on households' stock market participation status or portfolio allocation

¹⁵Please 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.

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. Our results indicate that all factors are statistically significant when pooling our consumption data and performing an OLS regression. This finding has two main implications. Firstly, we provide evidence of a positive correlation between stock returns and consumption at the daily frequency. Secondly, this result suggests that households in our sample should consider participating in the stock market, which is consistent with the CCAPM theory.¹⁶

Next, we include household fixed effects to consider the expenditure variations across households and control for all household factors that do not vary over time. 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 the fluctuation in systematic risks while they engage in spending, thereby underscoring the relevance of our consumption data for the purpose of testing the CCAPM.

3 Asset Pricing with Daily Shopper Spending

3.1 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 hard to measure accurately in the data, 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 data because those are the only available data conventionally. 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. Aggregating data also contaminates

¹⁶Mankiw 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, male head education, marital status, and TV items. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

<i>Panel A. Pooled OLS</i>		
	Factor Loadings	<i>t-stat</i>
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	
<i>Panel B. Household fixed effect</i>		
	Factor Loading	<i>t-stat</i>
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	

consumption data.¹⁷

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

¹⁷Breeden et al. (1989) and Ait-Sahalia et al. (2005) show that time aggregation leads to significant errors in

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.

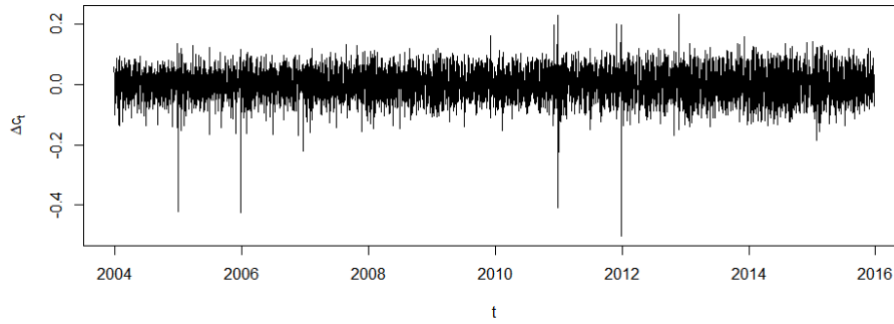
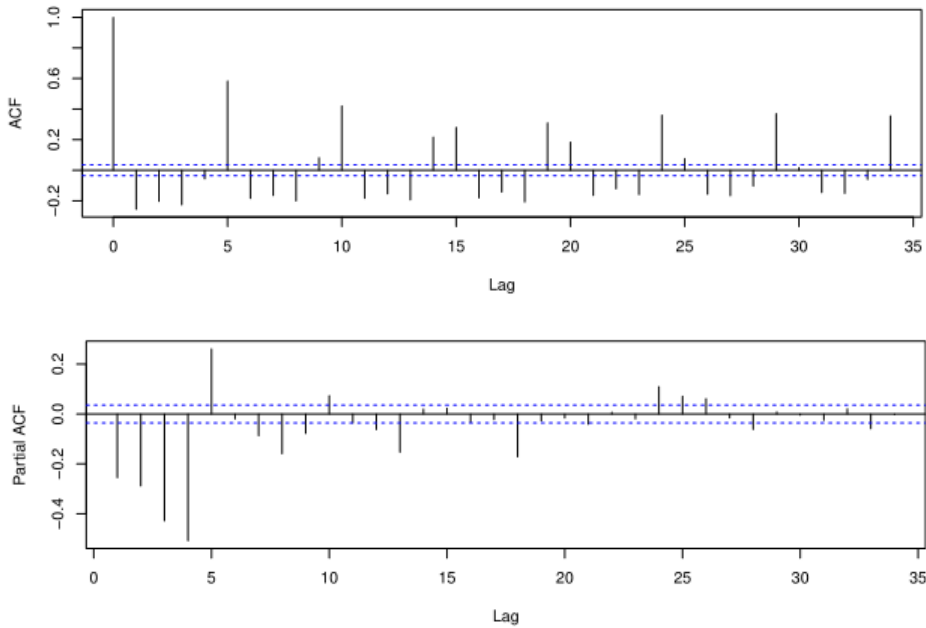


Figure 2 plots our daily consumption growth across our sample period from 2004 to 2015. We do not observe significant upward or downward time trends but strong high-frequency fluctuations around the constant level near zero, suggesting we should focus on the stochastic variance process instead of the mean.¹⁸

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.



consumption growth and stock returns, respectively.

¹⁸The 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 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 the time-series data and consumption usually relates to a slowly-moving macroeconomics environment, it is reasonable to 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 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 the information presents 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, which 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 aggregate the high-frequency consumption with low-frequency consumption, these fluctuations are 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. It 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

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

$$= \tau_{t-1} g_{t-1}. \quad (3)$$

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

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

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

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

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

Although logarithm transformation is not a linear function, it is a monotonic function, which suggests 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

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

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 short-run dynamics. Based on Equation (6), we find that *ceteris paribus*, ignoring 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 as a product of 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.¹⁹ Following Engle and Rangel (2008), we allow the data to provide 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:

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

$$h_t = \tau_t g_t, \quad (9)$$

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

$$\tau_t = \exp(f_1(t)). \quad (11)$$

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

¹⁹Boons 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

$$E(\epsilon_t^2) = \tau_t. \quad (12)$$

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.²⁰

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 $f_1(d)$.

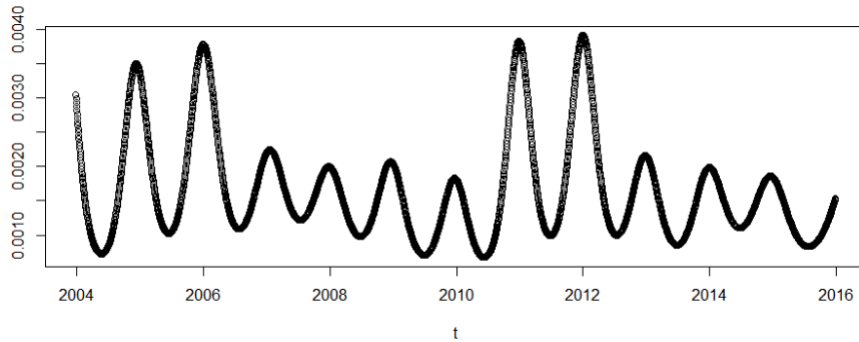


Figure 4 shows the fitted values of low-frequency variance (τ_t) with only ($f_1(d)$). The plot has a very odd-looking rise-and-fall pattern, suggesting strong intra-annual fluctuations exist. We expect to see the smoothness of a long-term trend; thus, the rise and fall pattern contradicts the long-term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

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

²⁰Knot points are the points where 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 , which represents 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 a 1% level, suggesting that the AR-spline-GARCH model in Equations (8)-(10) fits well with our data.

Figure 5 shows the fitted value of two smooth functions ($f_1(t) + f_2(d)$) 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. For the long-term trend, it 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). 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 .

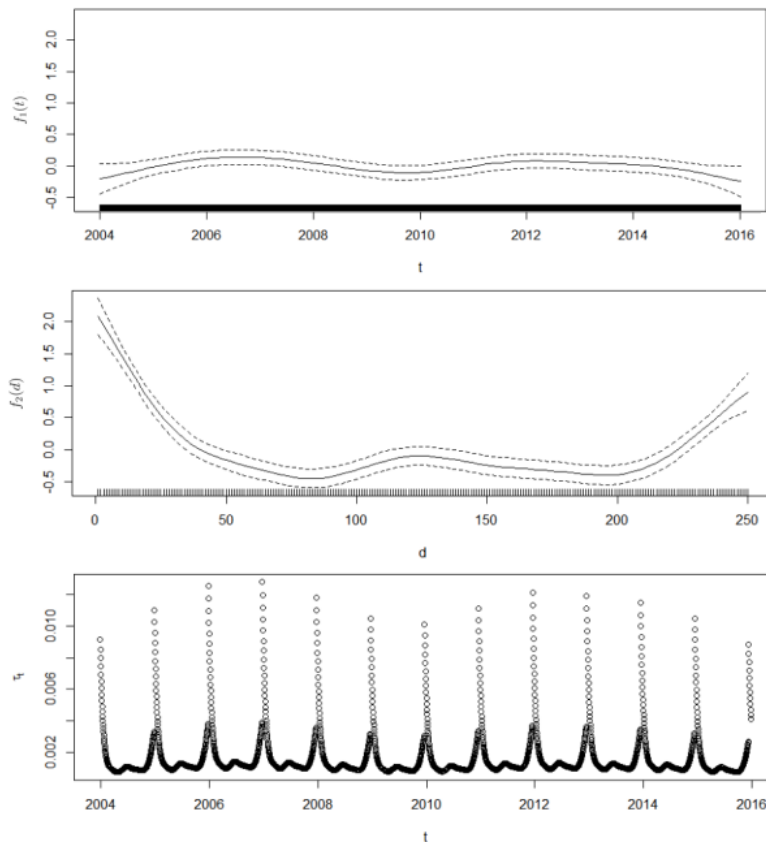


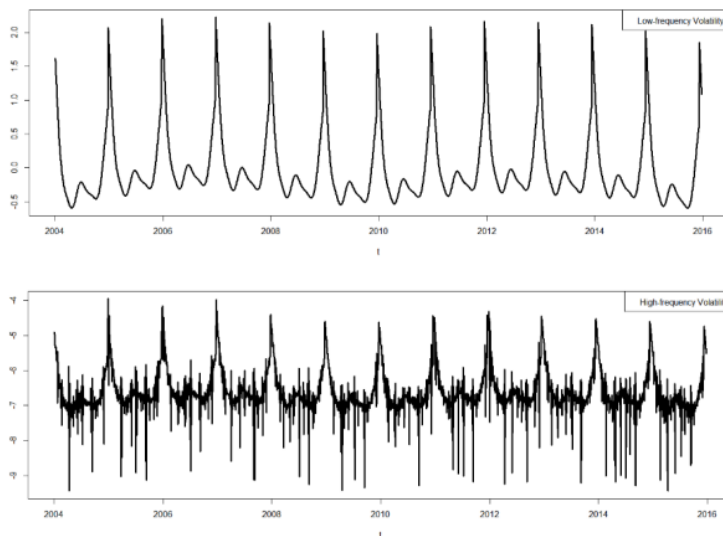
Figure 6 plots the logarithm of the fitted value of low-frequency variance (τ_t) and high-frequency variance (h_t) of our data during the sample period using the AR-spline-GARCH model. The graph shows strong intra-annual fluctuations ($f_2(d)$) and short-run dynamics (g_t). Based on the model's fit,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

3.2 The Equity Premium and Risk-Free Rate

We consider a representative agent with additive CRRA preferences in our economy. Empirical evidence suggests that with the power utility, an implausibly high level of risk aversion is required

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

This figure shows the fitted value of low-frequency variance (τ_t) and high-frequency variance (h_t), 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 .



to fit the equity premium, given that the 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 classic model using our consumption data with the Euler equation of consumption:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R_{t+1}^e] = 0, \quad (14)$$

where C_t is daily consumption at time t , β is the subjective discount factor, γ is the relative risk aversion coefficient, and R_{t+1}^e 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:

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

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:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma} R_{t+1}^e] = 0, \quad (16)$$

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma} R_{t+1}^f] = 1, \quad (17)$$

where R_{t+1}^f 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 the 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:

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

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 logged 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% . The mean absolute pricing error for all these

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:

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

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:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma} R_{t+1}^e] = 0, \quad E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma} R_{t+1}^f] = 1.$$

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 logged log price to dividend ratio. The moment restrictions are as follows:

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

where β is set to be 0.95, R_{t+1}^e 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)
<i>Panel A. Equity Premium (Exactly Identified)</i>					
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				
<i>Panel B. Equity Premium and Risk-Free Rate (One-Stage GMM)</i>					
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 <i>p-value</i>	0.232	0.630	0.390	0.120	0.550
Observations	3021				
<i>Panel C. Equity Premium and Instruments (One-Stage GMM)</i>					
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 <i>p-value</i>	0.598	0.950	24	0.250	0.240
Observations	3020				

models is zero.

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 T-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 as conditioning 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 among all measures. This result reconciles the difference in risk aversion estimates between the household finance and empirical asset pricing literature. Household finance literature usually considers a relative risk aversion coefficient of less than 10, while empirical asset pricing literature considers a relative risk aversion coefficient greater than 10. Meanwhile, the implied risk-free rate is 0.003%, closest to the empirically observed average risk-free rate.²¹ 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 resulting risk-free rate is found to be considerably lower compared to 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 detail in Section 3.1.

²¹In our sample period, the observed risk-free rate was 0.005% on average.

3.3 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

$$E[R_{i,t+1}^e] = \lambda + \lambda_c \beta_i, \quad (19)$$

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-free 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 time-varying consumption beta:

$$R_{i,t+1}^e = \alpha_i + \beta_{i,c} \log\left(\frac{C_{t+1}}{C_t}\right) + \epsilon_{i,t+1}. \quad (20)$$

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:

$$E[R_{i,t+1}^e] = \lambda_c \beta_{i,c}. \quad (21)$$

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, 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, Nagel, and Shanken (2010). This selection of two testing asset groups (31 and 35 portfolios) shows an economically important cross-section. Black, Jensen, and Scholes (1972) raise the concern that first-stage betas are measured with errors; thus, using portfolios as test assets is better.

Utilizing portfolios as test assets is associated with certain limitations. One prominent challenge pertains to the reduction in test power that results from the diminished dimensionality associated with the utilization of portfolios. That is to say, the mean returns of portfolios are subject to changes in fewer explanatory factors compared to individual stocks. Furthermore, diversification into portfolios might potentially 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. If this linear relationship is rejected, it suggests that the index is not positioned on the frontier. However, if the individual assets are consolidated into portfolios that are sorted by beta, any asset pricing errors across individual assets that are not related to the beta are unlikely to be identified. Thus, this technique could potentially yield an incorrect inference if the index is situated on the efficient frontier generated using beta-sorted portfolios.

To overcome the limitations of employing portfolios as testing assets, we utilize individual stocks instead. However, the Fama-MacBeth regression method is susceptible to an EIV bias when testing asset pricing models. To mitigate this bias, we employ the instrumental variable (IV) approach, as suggested by Jegadeesh et al. (2019). In particular, we partition the entire sample into subsamples based on odd- and even-numbered months. 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 month betas as IV (instrumental variable) betas and even-numbered month 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 1 is an $N \times 1$ vector of ones.

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

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

where R_t is the excess return for even-numbered months 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. Correspondingly, we take the betas in the even-numbered month subsample as the IVs for each odd-numbered month and estimate the same regression to obtain the FMP. To perform the IV method, we utilize daily returns from both odd and even months over a rolling three-year estimation period to estimate betas so that the measurement error in the instrumental variable and explanatory variables are not correlated cross-sectionally. We fit the second-stage cross-sectional regression each month using the IV estimator.

We follow the screening criteria of Gu, Kelly, and Xiu (2020) 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). To examine the asset pricing implications, we utilize 31 portfolios consisting of ten sizes, ten book-to-market, ten profitability, and one equity premium as test assets, as well as the 167 testing assets proposed by Giglio and Xiu (2021).²²

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.²⁴

In model (1), Table 5, Panel A, we report cross-sectional tests using above-mentioned 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, robust-minus-weak, and conservative minus aggressive. 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 premia are all positive and range from 0.739 to 1.289 across different specifications, implying that investors consistently command a premium to hold assets with high consumption risk after controlling for other common risk factors.

²²The 167 portfolios is a subset of the testing assets that Giglio and Xiu (2021) use. We do not include all of 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.

²³We use the formula, $4(\frac{T}{100})^{\frac{2}{5}}$, to find the optimal number of lags for Newey-West t -statistics.

²⁴The results are available upon request.

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 a 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.²³ We also report the mean absolute pricing error (MAPE). The sample period is from 2004 to 2015. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

<i>Panel A. 31 Portfolios</i>					
	(1)	(2)	(3)	(4)	(5)
Δc_t	1.289** (0.573)	1.208** (0.479)	0.739** (0.371)	0.810** (0.375)	
MRF		0.006 (0.026)	0.029 (0.027)	0.045* (0.024)	0.043* (0.024)
SMB			-0.002 (0.009)	0.006 (0.009)	0.006 (0.009)
HML			-0.005 (0.011)	-0.001 (0.011)	-0.002 (0.011)
CMA				0.010 (0.010)	0.010 (0.010)
RMW				-0.004 (0.006)	-0.002 (0.006)
UMD				0.070*** (0.025)	0.065*** (0.024)
Constant	0.035* (0.018)	0.026 (0.020)	0.004 (0.023)	-0.012 (0.018)	-0.010 (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
<i>Panel B. 35 Portfolios</i>					
	(1)	(2)	(3)	(4)	(5)
Δc_t	1.668*** (0.612)	1.394** (0.526)	0.777* (0.391)	0.658* (0.383)	
MRF		-0.053 (0.050)	0.006 (0.020)	-0.076 (0.052)	0.003 (0.028)
SMB			-0.003 (0.008)	0.007 (0.011)	0.003 (0.009)
HML			-0.007 (0.007)	-0.054* (0.028)	-0.000 (0.011)
CMA				0.045*** (0.017)	0.010 (0.009)
RMW				0.023 (0.015)	0.004 (0.008)
UMD				0.101*** (0.029)	0.068*** (0.025)
Constant	0.043** (0.018)	0.068** (0.028)	0.033* (0.017)	0.078** (0.035)	0.032 (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

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.

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. 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. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

	<i>Individual Stocks</i>				
	(1)	(2)	(3)	(4)	(5)
Δc_t	0.458*** (0.130)	0.496*** (0.088)	0.257*** (0.079)	0.320*** (0.067)	
MRF		0.007 (0.012)	0.013 (0.010)	0.028*** (0.008)	0.031** (0.013)
SMB			-0.008 (0.006)	-0.000 (0.003)	0.002 (0.005)
HML			-0.020*** (0.007)	-0.013** (0.006)	-0.011 (0.006)
CMA				0.010** (0.004)	0.005 (0.003)
RMW				-0.004* (0.003)	-0.007* (0.005)
UMD				0.076*** (0.006)	0.073*** (0.010)
$\log(\text{Market Value of Equity})$	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.000 (0.001)	-0.003*** (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 (0.016)	0.027*** (0.007)	0.030*** (0.008)	0.008 (0.008)	0.010 (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 0.47% in the one-factor model, which is lower than the portfolio models and might be due to the higher volatility of individual stock returns than

that of 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 167 portfolios as used by Giglio and Xiu (2021) (see Footnote 20). We repeat the regressions in models (1) and (4) using these assets, and all λ_c s are significant at the 5% level. We do not report these results here for brevity but can make them available upon request.

3.4 Consumption Mimicking Portfolio Tests from 1960 to 2015

Our entire sample period is from 2004 to 2018 and the primary sample period is between 2004 and 2015, implying the out-of-sample period 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 1960.²⁵

We aggregate our daily CMP into annual frequency and compare its performance with other annual consumption measures from 1960 to 2014 when these measures have data available.²⁶ Later, in Section 6.2, we show the performance of our CMP on a daily frequency from 2004 to 2015, our in-sample period.

The mimicking portfolio approach can alleviate the inflated price of risk due to the measurement errors of non-tradable assets. To demonstrate,

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

where Δc_t is consumption growth, CMP is consumption-mimicking portfolios, and $\text{cov}(R_t, \varepsilon_t) = 0$ for any excess return, R_t . The term ε_t is noise and orthogonal to the returns; therefore, it deflates

²⁵We thank Professor Alexi Savov for this suggestion.

²⁶To alleviate the aggregation bias, we use the fourth-quarter year-over-year CMP as our annual growth measure.

the beta estimates and the estimated risk price (see Adrian et al. (2014); Pukthuanthong et al. (2021)).

It is noteworthy that ε_t does not affect the covariances between returns and Δc_t and 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 $var(\Delta c)/var(CMP)$, the amount by which the cross-sectional price of risk (λ) is inflated to compensate precisely.

Our study performs the CCAPM test using CMP compared with other measures in this section and a robustness check in Section 6.2. To construct CMP, we project our Δc_t onto the space of excess returns using the following time-series regression:

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

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, over ten years), medium-term (MTGovBond, 1 to 10 years), short-term government bonds (STGovBond, one year or less), and low-grade or high-yield corporate bonds (LowGradeCorpBond), respectively, from the Datastream. We choose these returns as they are commonly applied by researchers 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, defined as the fitted value of Equation (10).

We normalize the weights, Γ , to sum to one to make it more convenient for units. The FMP return is given by

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

and $\hat{\Gamma} = \frac{\Gamma}{\sum \Gamma}$ using OLS from the daily data from 2004 to 2015. Our approach is the time-series approach introduced by Lamont (2001), a common approach of mimicking portfolio constructions.

We multiply normalized weights ($\hat{\Gamma}$) to 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 that our measure yields 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 3.3. We additionally report the GMM test for 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 1960-2015	Annual Δc_t CMP 1960-2014	Garbage 1960-2007	Unfiltered NIPA 1960-2014	P-J Dec-Dec 1960-2014	Q4-Q4 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
<i>z-stat</i>	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 if 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 CMP in explaining the cross-section of stock returns is inferior to its original daily measure. As argued in Section 3.1, 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 Δc_t CMP denotes our daily consumption growth in 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 a 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. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

	<i>Panel A 31 Portfolios</i>					<i>Panel B 35 Portfolios</i>				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Annual CMP Δc_t	-0.059 (0.200)	-0.045 (0.203)	-0.173 (0.186)	0.425 (0.297)	0.406 (0.335)	-0.326 (0.209)	-0.294 (0.215)	-0.209 (0.188)	0.494* (0.294)	0.353 (0.314)
MRF	-0.000 (0.041)	0.004 (0.037)	-0.032 (0.043)	0.006 (0.052)		-0.084** (0.041)	-0.068 (0.041)	-0.049 (0.036)	-0.029 (0.042)	
SMB	0.034 (0.024)	0.034 (0.024)	0.032 (0.025)			0.039 (0.024)	0.036 (0.025)	0.036 (0.024)		
HML	0.036* (0.018)	0.035* (0.019)	0.036 (0.019)			0.041** (0.017)	0.042** (0.017)	0.039** (0.017)		
RMW	0.023** (0.010)	0.023** (0.010)				-0.001 (0.018)	-0.005 (0.017)			
CMA	-0.020 (0.021)	-0.019 (0.021)				0.018 (0.016)	0.024 (0.017)			
UMD	-0.022 (0.040)					-0.047 (0.041)				
Constant	1.057*** (0.037)	1.053*** (0.031)	1.084*** (0.040)	1.061*** (0.048)	1.055*** (0.020)	1.132*** (0.033)	1.117*** (0.033)	1.100*** (0.029)	1.102*** (0.036)	1.065*** (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

3.5 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 path, 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 issue is commonly known as the “Limited T versus Large N” problem. Should the betas be jointly zero or display no variation, the risk premium would be subject to bias. The literature predominantly utilizes annual consumption measures commencing from the postwar era of 1960. Consequently, the most frequently used testing assets comprise between 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 filtered NIPA, P-J, Q4-Q4, Garbage, and a filtered NIPA, revealing that only Garbage successfully passes the rank test.²⁷

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 the 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 a 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)	Unfiltered 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 0.073, rejecting the null at the 10% level. We also conduct individual stock tests for other annual measures. However, due to 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) between 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 PERMNOs. None of

²⁷See Table III in KZ, where they use 31 portfolios as testing assets.

the p -values of the rank tests for other measures are significant.

4 Magnet, and Non-Food Grocery and General Merchandise

This section of our study exploits our dataset’s rich granularity, allowing us to examine over two million distinct products. As 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 Universal Product Codes 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 those with the opposite characteristics, specifically those that can be stored for extended periods, such as non-food grocery and general merchandise.²⁸ We define the latter as relatively durable goods from two perspectives: first, certain 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), who 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.

We test our hypothesis by applying each household’s consumption activities on Magnet products and relatively durable goods. There is a caveat. Nielsen did not start collecting data on

²⁸These 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 vehicle, and office supplies, which could be considered as semi-durable goods in our data.

Magnet products until 2007, and even during that year, such products were sparsely reported because of 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. We report primary and extended results in Table 10, Panels A and B.

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 9.219 at 1% significance from relatively durable goods and all products from the primary sample. This lower relative risk aversion coefficient generated by Magnet products consumption relative to Relatively Durable Goods consumption is consistent with Campbell (2018) 's argument and supports our initial prediction.

However, Panel A also shows a negative covariance and correlation between Magnet products consumption and excess market returns. This abnormal coefficient might be attributed to the shortage of Magnet products consumption data. As illustrated, Nielsen does not well report Magnet products during 2007, and only eight years of data are available in Panel A, which might introduce noises to the 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 Panel A, further supporting our hypothesis.

Table 10: Magnet Products, and Non-Food 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 3 (main sample). Nielsen defines magnet products as products that do not have regular UPCs. Relatively durable goods, including Non-food 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_{t+1}^e is the value-weighted CRSP index return over the daily risk-free rate. See the estimation method described in Section 3.2 and Table 3. Panels A and B present the result from the sample ending in 2015 and 2018, respectively.

<i>Panel A: Sample ending 2015</i>			
	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
<i>z</i> -stat	1.862	4.239	3.042
Implied r_f	-0.170%	-0.440%	-0.091%
Observations	2258	3021	3021
<i>Panel B: Sample ending 2018</i>			
	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
<i>z</i> -stat	2.608	3.608	2.152
Implied r_f	-0.258%	-0.430%	-0.103%
Observations	3010	3010	3010

5 Out-of-Sample Tests

Strong results should sustain across periods (Schwert (1990)). To check out-of-sample robustness, 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; 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 considering 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 Panel 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 0.470% in Table 6 to 0.236% in Table 12. Meanwhile, all λ_c s are significant across all panels at either 10% or 1%. 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:

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

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

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R_{t+1}^e] = 0, \quad E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R_{t+1}^f] = 1.$$

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 logged log price to dividend ratio. The moment restrictions are as follows:

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

We fix β to be 0.95. R_{t+1}^e is the value-weighted CRSP index return over 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	
<i>Panel A. Equity Premium (Exactly Identified)</i>	
RRA (γ)	17.954
(s.e.)	6.808
<i>z-stat</i>	2.637
MAE	0.562
Implied r_f (%)	-0.320
Observations	753
<i>Panel B. Equity Premium and Risk-Free Rate (One-Stage GMM)</i>	
RRA (γ)	5.925
(s.e.)	0.378
<i>z-stat</i>	15.683
MAE	0.431
J-test <i>p-value</i>	0.695
Observations	753
<i>Panel C. Equity Premium and Instruments (One-Stage GMM)</i>	
RRA (γ)	11.957
(s.e.)	7.121
<i>z-stat</i>	1.679
MAE	0.562
Implied r_f (%)	-0.110
J-test <i>p-value</i>	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 a 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). We include 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). * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

	<i>Panel A. 31 Portfolios</i>	<i>Panel B. 35 Portfolios</i>	<i>Panel C. Individual Stocks</i>
	(1)	(2)	(3)
Δc_t	0.715*	0.553*	0.236***
	(0.417)	(0.332)	(0.087)
$\log(\text{Market Value of Equity})$			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

6 Applications

6.1 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.

To create the consumption risk hedging portfolio, we adopt the approach of Engle et al. (2020). 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. The Consumer Panel Database (CPD) provides universal product codes (UPCs) for household products from 2004 to 2015. We leverage the GS1 Company Database (GEPiR) to link the products recorded in the CPD to the

firms via UPC barcodes. The ultimate parents' name for UPC barcodes is obtained through GEPIR, the sole US 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 their ability to reveal sales growth at this high frequency, and thus enable the development of the consumption risk hedging portfolio.²⁹ We then aggregate all the products' 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 . 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:

$$R_{it} = \alpha + \beta_{\Delta c_{it}} \times \Delta c_{it}, \quad (25)$$

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 and denote it 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).³⁰ The portfolio returns can be written as

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

where r_t are the excess returns of individual stocks and Z_t are the firm-level characteristics. We consider these portfolios as the sum of the monthly weighted returns of each firm based on the

²⁹PERMNO is a unique permanent security identification number assigned by CRSP to each security.

³⁰The results remain qualitatively the same if we standardize all the characteristics cross-sectionally by month.

consumption beta, B/M, size, and market, respectively.

Next, we examine which firms provide high returns during high uncertainty. We relate high economic uncertainty to consumption growth and define a high economic uncertainty period as a period where consumption growth (Δc_t) is low or stagnant. We define consumption risk (hereafter, CR_t) as one minus consumption growth (Δc_t) 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) presents *firm-level* consumption risk exposure whereas $1 - \Delta c_t$ or CR_t presents *aggregate* consumption risk exposure.

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

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

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, we use 2016 as an example because it is 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:

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

Finally, we integrate the weights of the firms with those of the industries and rank the resulting

portfolio weights in Panel B of Table 13. Our findings reveal that investors should adopt long positions in industrial and commercial machinery and computer equipment firms to hedge against consumption risk while simultaneously divesting from food and beverage stocks. Consumption outlays on industrial and commercial machinery, and computer equipment may be attributed to the market's increasing consumption, and consequently, acquiring these products carries a negligible market consumption risk. On the other hand, expenditure on food and related products is associated with low consumption growth (high consumption risk), given that they are deemed necessities and their prices are significantly lower. Notwithstanding the considerable consumption risk, food and related items must still be purchased.

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 6.1 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 6.1 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		Panel B. Industry's Weights based on Firm Individual Consumption Hedging Portfolio Weights	
	CR_t	Sic 2 Code	Industry
			<i>Positive Weights</i>
$Z_{t-1}^{low-cons-risk'} r_t$	0.043*** (0.016)	35	Industrial and Commercial Machinery and Computer Equipment
$Z_{t-1}^{BM'} r_t$	0.039 (0.031)	36	Electronic & Other Electrical Equipment & Components
$Z_{t-1}^{size'} r_t$	-0.002 (0.039)	23	Apparel, Finished Products from Fabrics & Similar Materials
$Z_{t-1}^{Market'} r_t$	-0.046 (0.032)	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
Observations	143	50	Wholesale Trade - Durable Goods
R^2	0.079	33	Primary Metal Industries
F-statistics	2.965	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
			<i>Negative Weights</i>
		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

6.2 Tradable Consumption Factor

To ensure the robustness of our findings, we have constructed a consumption-mimicking portfolio (CMP), as outlined in Section 3.4, and have made it available on our website. In this section, we present the performance of the CMP at the daily level, with a focus on assessing its effectiveness in an in-sample context.

We follow the same CMP approach as in Section 3.4, but limit our analysis to the sample period from 2004 to 2015. 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. For the cross-sectional tests, we consider various testing assets, including 35 portfolios that comprise 25 size and book-to-market sorted portfolios, as well as ten industry portfolios. We also examine 31 portfolios consisting of 10 sizes, ten book-to-market, ten investment growth sorted, and one market portfolio, individual stocks, and the 2805 single characteristics-sorted q-portfolios. For individual stocks, we also apply Jegadeesh et al. (2019)'s approach as explained in Section 3.3. We employ six size-BM momentum sorted and four bond portfolios as the base assets used to construct our CMP. Moreover, we expand the asset space by considering.³¹

Panel A of Table 14 reports the GMM test. The in-sample daily CMP yields a risk aversion coefficient of 4.142, which is lower than the raw daily CG. We attribute this superior performance to the composition of CMP, which includes assets that move closely with the market and the in-sample property of 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.

³¹q-portfolios are double-sorted portfolios based on size and characteristics from Lu Zhang's q-factor model data library, which result in over 2800 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, (4) individual stocks; which are the base assets that we use to construct our CMP; (5) 2805 single characteristics-sorted q-portfolios to expand the asset space. 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		
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
RRA	4.142											
(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

7 Additional Robustness Tests

7.1 Decomposition of Daily Consumption Growth

In light of potential concerns regarding the influence of seasonal trends on consumption growth and its effects on our findings, we undertake a decomposition analysis to isolate the weekly seasonality effect from the daily consumption series. The purpose of this analysis is 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 that may exist.

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 (9.219). The inclusion of the observed risk-free rate reduces the risk aversion estimate further to 3.65, which represents a marked improvement compared to the estimate for raw consumption growth (11.477). Moreover, the use of instruments reduces the risk aversion estimate, albeit insignificantly, as evidenced by the standard error of 30.426.

Panel B of Table 15 shows the risk premia of deseasonalized consumption growth against various testing assets. The λ_c are consistently significant at 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 only using 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 upon 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) 2805 single characteristics-sorted q-portfolios to expand the asset space; (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-Seasonality	Panel B: Fama-MacBeth	31 Portfolios	35 Portfolios	Q Portfolios	Individual Stocks
<i>Equity Premium (Exactly Identified)</i>						
RRA (γ)	11.133	CG-Seasonality	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)
<i>Equity Premium and Risk-free Rate (One-stage GMM)</i>						
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)
<i>Equity Premium and Instruments (One-stage GMM)</i>						
RRA (γ)	1.144	Observations	92,101	103,985	8,287,771	10,814,041
(s.e.)	30.426	R^2	0.192	0.173	0.175	0.069
t stat	0.038	MAPE	0.036	0.037	0.04	0.022
MAE	0.0028					
Implied r_f	0.053%					
J-test p -value	0.157					

7.2 Expenditure-sorted Consumption Growth

In testing the relationship between households' expenditures and their risk aversion estimates, we confront the challenge of unavailable household wealth information. As Ait-Sahalia, Parker, and Yogo (2004) suggest, households that allocate a larger share of their wealth to consumption expenditures should exhibit lower risk aversion relative to those who spend 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, lend support to 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.

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.

<i>Panel A. Equity Premium (Exactly Identified)</i>				
	Top Decile Consumption	Bottom Decile Consumption	Above Median Consumption	Below Median Consumption
RRA (γ)	8.006	13.317	9.078	12.023
(s.e.)	2.443	8.873	2.922	7.188
<i>t-stat</i>	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
<i>Panel B. Equity Premium and Risk-free Rate (One-stage GMM)</i>				
	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
<i>t-stat</i>	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
<i>Panel C. Equity Premium and Instruments (One-stage GMM)</i>				
	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
<i>t-stat</i>	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

7.3 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 if the results hold using weekly data. The consumption of households happens daily; thus, the daily measure is the suitable horizon, confirmed

by the pattern we observe in the 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 day consumption of a week.^{32,33} First, we present the summary statistics in Table 17. Column 2 reports the summary statistics for weekly consumption growth. To facilitate comparison, we report the summary statistics again for daily consumption growth and 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 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.

	<i>Panel A. Sample Period (2004-2015)</i>					<i>Panel B. Sample Period (1960-2014)</i>			
	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

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 of 13.028, which is 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:

³²There is a strong likelihood of weekend consumption being different from weekday consumption. For example, during weekdays, households can be constrained by their working hours, whereas during weekends, households could have more hours available for consumption.

³³Our first weekly consumption growth observation is 01/07/2004. For the first weekly observation, the first day (01/01/2004) is Thursday, and the seventh day (01/07/2004) is Wednesday.

low-frequency aggregate consumption growth performs worse than higher-frequency consumption growth. The 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.³⁴

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:

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

where β is set to 0.95. R_{t+1}^e 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
<i>z-stat</i>	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				

Then we check whether weekly consumption growth can help us understand the observed cross-sectional variation in 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 of 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 with garbage data.

³⁴We 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.

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 the Fama-MacBeth test with many testing assets. We choose 120 portfolios to be consistent with the 5.640 T/N ratio from Kleibergen and Zhang (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 a 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. For all models, we report six-lag Newey-West t -statistic in brackets, and report mean absolute pricing error (MAPE). * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

<i>Panel A. 31 Portfolios</i>					
	(1)	(2)	(3)	(4)	(5)
Weekly Δc_t	0.004 (0.007)	0.004 (0.006)	-0.001 (0.005)	0.001 (0.005)	0.003 (0.004)
MRF		-0.000 (0.002)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)
SMB			0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
HML			-0.000 (0.001)	-0.000 (0.001)	-0.000 (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*** (0.001)	1.002*** (0.001)	1.001*** (0.001)	1.001*** (0.001)	1.000*** (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
<i>Panel B. 35 Portfolios</i>					
	(1)	(2)	(3)	(4)	(5)
Weekly Δc_t	0.011* (0.007)	0.013** (0.006)	0.001 (0.005)	-0.003 (0.005)	-0.005 (0.005)
MRF		-0.001 (0.002)	0.000 (0.001)	-0.000 (0.001)	0.000 (0.001)
SMB			0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
HML			-0.000 (0.001)	-0.000 (0.001)	-0.000 (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*** (0.001)	1.002*** (0.001)	1.002 (0.001)	1.002 (0.001)	1.001*** (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.)

<i>Panel C. 120 Portfolios</i>					
	(1)	(2)	(3)	(4)	(5)
Weekly Δc_t	0.031 (0.027)	0.089** (0.043)	0.130** (0.054)	0.049 (0.055)	0.082 (0.057)
MRF		0.110*** (0.006)	0.150*** (0.007)	0.194*** (0.007)	0.223*** (0.009)
SMB			0.005*** (0.001)	0.007*** (0.002)	0.009*** (0.002)
HML			0.016*** (0.003)	0.019*** (0.004)	0.030*** (0.004)
CMA				0.009*** (0.003)	0.006* (0.003)
RMW				0.006 (0.004)	-0.004 (0.004)
UMD					0.046*** (0.005)
Constant	0.982*** (0.002)	0.883*** (0.006)	0.850*** (0.070)	0.803*** (0.008)	0.777*** (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). * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

	<i>Individual Stocks</i>				
	(1)	(2)	(3)	(4)	(5)
Weekly Δc_t	0.003 (0.002)	0.003*** (0.001)	0.002** (0.001)	0.002** (0.001)	
MRF		-0.000 (0.001)	-0.000 (0.000)	0.000 (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*** (0.000)	0.002*** (0.000)
$\log(\text{Market Value of Equity})$	-0.002** (0.001)	-0.001 (0.001)	-0.003* (0.001)	0.003*** (0.001)	0.003*** (0.001)
Book to Market Ratio	0.000 (0.001)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Constant	1.001*** (0.001)	1.001*** (0.000)	1.002*** (0.000)	1.001*** (0.000)	1.001*** (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, serving as 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 not only 31/35 portfolios but also 120 characteristics-sorted portfolios and individual stocks. See Section 7.4 for the rationale and method we use to select these 120 portfolios. Weekly consumption performs well with a large number of 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 to be 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 with low-frequency consumption growth could lose a large amount of information. Ignoring this information results in measured consumption that is too smooth and with a much higher level of relative risk aversion.

8 Conclusion

Our study employs daily consumption as the basis for re-evaluating Euler equations within the standard consumption-based capital asset pricing model. Our results demonstrate that the use of daily consumption in the CCAPM produces an equity premium consistent with a relative risk aversion coefficient of 9.217. Furthermore, through joint pricing tests, a low-risk aversion coefficient of 5.159 emerges, indicating that daily consumption surpasses both garbage and unfiltered NIPA measures in resolving the equity-premium and risk-free-rate puzzles. In addition, our daily consumption-based model provides a cogent explanation of the cross-sectional dispersion in average returns.

Apart from 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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