Electricity Consumption and Asset Prices

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September 2010

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Abstract

Electricity consumption is a useful real-time proxy for economic activities, as most modern-day economic activities involve the use of electricity, which cannot be easily stored. Empirically, electricity consumption data is widely available in high frequency at both aggregate and disaggregate levels, allowing several interesting asset pricing applications. For example, we demonstrate that electricity usage is a better measure of spot consumption, as in the CCAPM, and that an electricity-based CCAPM does well in both time series and cross-sectional asset pricing tests. This result is not driven by electricity consumption due to production activities and extreme weather fluctuations. We also find that industrial usage of electricity, capturing business cycle variation in real time, predicts future stock excess returns at both market and industry level.

JEL classification: G12, G17

Keywords: Consumption-based Capital Asset Pricing Model (CCAPM), electricity consumption, return predictability.

A fundamental question in financial economics is how economic activities such as consumption and production and the related business cycle fluctuations affect asset prices. While a long strand of literature has made successful attempts to address this question from a theoretical prospective, empirical attempts to link economic activities to asset pricing have had less success. For example, the growth rate in the standard NIPA consumption measure (real per capita personal expenditure on nondurable goods and services) is too smooth to justify the observed equity risk premium in the U.S. (Mehra and Prescott (1985)). In addition, traditional macroeconomic variables have performed dismally at predicting future stock returns (Lettau and Ludvigson (2001)). In this paper, we examine electricity usage as a new real-time proxy of economic activities. We find that electricity usage can explain stock returns in both time series and cross-section within the consumption-based asset pricing framework. It also captures business cycle fluctuations and predicts future stock excess returns.

In modern life, most economic activities involve the use of electricity. For example, when preparing a meal, food may have been stored in a freezer, defrosted in a microwave oven, cooked in an electric oven, and eaten while watching a sports game aired on TV. Shopping malls and restaurants may use extra electricity during the winter holiday season to be open longer hours and to power ornamental lights. We, therefore, expect residential and commercial usage of electricity to be a good proxy for consumption. In addition, factories typically use electricity in production, suggesting industrial usage of electricity to be a good proxy for economic output and business cycle fluctuations. For example, Comin and Gertler (2006) use electricity usage to measure production activity in their study of the business cycle. Importantly, due to technological limitations, electricity cannot be easily stored: once produced, it has to be either consumed or wasted. As a result, electricity usage is more likely to track economic activities in real time.

Since electric utilities are highly regulated and are subject to extensive disclosure requirements, electricity usage data are accurately measured at high frequency and are available at a disaggregated level. In the United States, monthly electricity consumption information is available from 1960 to the present, by state and by user type. In the United Kingdom, electricity consumption information is available by half-hours since 2001, and daily since 1970. In the EU, monthly electricity consumption is available from 1990 to the present. Annual electricity consumption is available for many other countries in the world. Taking advantage of the availability of electricity consumption data, we examine several asset pricing applications empirically.

In the first application, we examine electricity usage as a proxy for aggregate consumption in the context of the standard Consumption-based Capital Asset Pricing Model (CCAPM) of Lucas (1978) and Breeden (1979). In an effort to reconcile the observed high equity premium and low consumption risk within the CCAPM framework, extant literature has explored modifications in investor preferences, implications of incomplete markets, market imperfections, and alternative ways of measuring aggregate consumption risk.[1] Recently, Savov (2010) proposed an alternative approach using annual garbage generation as a measure of consumption; this measure is twice as volatile as the standard NIPA consumption measure and highly correlated with market returns. As a result, this measure yields a more modest implied relative risk aversion coefficient than conventional NIPA consumption expenditures. We

[1] Related papers include Sundaresan (1989), Constantinides (1990), Epstein and Zin (1991), Campbell and Cochrane (1999), Bansal and Yaron (2004), Hansen, Heaton, and Li (2008), Malloy, Moskowitz, and Vissing-Jorgensen (2009)), Constantinides and Duffie (1996), Mankiw and Zeldes (1991), Constantinides, Donaldson, and Mehra (2002), Ait-Sahalia, Parker, and Yogo (2004), Parker and Julliard (2005), Jagannathan and Wang (2007), and Jagannathan, Takehara, and Wang (2007).

complement Savov (2010) by showing that a simple and novel measure of consumption goes a long way in resurrecting the standard CCAPM.

Compared to existing consumption measures, including garbage generation, electricity consumption has at least three advantages which make it potentially a better candidate for testing the standard CCAPM.

First, we expect electricity consumption to reflect investors' consumption activities in real time. In contrast, the popular NIPA consumption data is smoothed with the X-11 seasonal adjustment. As forcefully argued by Ferson and Harvey (1992), "Obviously, one does not purchase goods at seasonally adjusted prices… seasonal adjustment can induce spurious correlation… leading to bias and erroneous inferences."

Second, electricity usage correctly measures consumption over the life of the product. Consumers derive utility from consumer products not at the time of purchase, but rather continuously over the life of the product. For example, the garbage generation measure would treat the purchase of a new TV set as a one-time consumption, registering it only when the new owner throws out the packaging.

Third, as previously discussed, electricity usage data are accurately measured at high frequency and are available at several disaggregated levels, allowing more potential applications than, for example garbage generation, which is only available at annual frequency by types of waste. High-frequency seasonally-unadjusted electricity consumption data get us one step closer to measuring the instantaneous ("spot") consumption as modeled in the CCAPM, thus minimizing the "summation" bias as studied by Breeden, Gibbons, and Litzenberger (1989). In this paper, we focus on the year-on-year annual growth rate using monthly electricity consumption data, for example, December this year to December next year. This growth rate calculation alleviates the impact of weather-induced within-year seasonal variation in electricity usage.

While we focus on *total* electricity usage as a measure of consumption since it is widely available for many countries, we confirm that, in the U.S., excluding industrial electricity usage, which measures production more than consumption, hardly alters our main results. In contrast, the garbage generation used in Savov (2010), which is estimated with the help of production data, is highly correlated with industrial electricity usage (72.8%) and less correlated with residential and commercial electricity usage (12.0% and 22.3%, respectively).

Using electricity consumption data, we find strong supporting evidence for the CCAPM in both time series and cross-section tests and in the U.S. and selected European countries.

In the U.S. during our sampling period from 1961 to 2008, the annual per capita total electricity consumption growth rate measured using December electricity consumption is 2.5 times more volatile than the standard NIPA consumption measure and is highly correlated with stock market returns. As a result, December to December total electricity consumption growth can match the equity premium with a relative risk aversion of 17.3 (and residential electricity consumption growth can match it with one of 12.4), which is on par with the risk aversion of 17 reported in Savov (2010) using garbage growth data and much lower than the 42.7 risk aversion associated with the annual NIPA expenditure. While the implied annual risk-free rate of 17.5 percent is still high, it is comparable to numbers associated with the garbage growth data and is much lower than those rates implied by the annual NIPA expenditure, which are often greater than 100 percent. We confirm the robustness of these time series results using different Generalized Method of Moments (GMM) specifications with different instruments and test assets.

In the cross section, we run Fama-MacBeth (1973) regressions on the 25 Fama and French (1992) size and book-to-market portfolios. We document a positive and significant consumption risk premium using December to December annual electricity growth rates. In a horse race, the electricity growth drives out both NIPA expenditure growth and garbage growth. In terms of average pricing errors in the cross-section, electricity growth underperforms the fourth quarter year-on-year expenditure growth measure of Jagannathan and Wang (2007) and the ultimate consumption risk measure of Parker and Julliard (2005), but outperforms other measures of consumption risk. Finally, model misspecification tests based on Hansen-Jagannathan (1997) distance also provide strong support for the electricity-based CCAPM.

In the second application, we examine two extensions of the standard CCAPM. The availability of electricity usage and stock excess return data at monthly frequency in the U.S. and several European countries allows us to re-examine the calendar effect associated with consumption as studied in Jagannathan and Wang (2007) and Jagannathan, Takehara, and Wang (2007). Complementing their cross-sectional evidence, we find December to December electricity consumption growth to perform better in the U.S., while April to April electricity consumption growth performs better in the U.K. and other European countries in time series tests. December coincides with the end of the tax year and the winter holiday in the U.S., while April coincides with the end of the tax year in the U.K. and the Easter holiday throughout Europe. As investors feel the need and have more leisure time to review their consumption and portfolio choice decisions during these times, the CCAPM should perform better. Our findings thus support the optimal inattention to the stock market discussed in Abel, Eberly, and Panageas (2007).

Taking advantage of the availability of state-level annual electricity usage data in the U.S., we test the model of Constantinides and Duffie (1996) based on uninsurable income shocks. We consider electricity usage in a state as a proxy for the consumption of a synthetic cohort in that state. Within this framework, we can match the equity premium with a relative risk aversion of about 18 during the period of 1961-2008. The required risk aversion parameter is similar to that found by Jacobs, Pallage, and Robe (2005), who use alternative state-level consumption data based on retail sales. The results confirm that electricity usage is indeed a good measure of consumption at both the aggregate and the state level. In addition, the fact that aggregate U.S. electricity consumption and state-level electricity consumption data yield similar required risk aversion parameters suggests that the incomplete market assumption might not be necessary when aggregate consumption is better measured. Finally, by linking state-level electricity growth to state-level weather fluctuations, we also confirm that weather change is unlikely to be driving the main results in our paper.

In the third application, we examine the performance of the electricity growth rate in predicting future stock excess returns. The question of return predictability is central for asset pricing, portfolio choice, and risk management. The general finding in the literature is that only financial indicators, not macroeconomic business cycle indicators, predict stock returns (see Campbell (2003), Cochrane (2007), and Lettau and Ludvigson (2009), among others). This finding is discomfiting, as expected returns should ultimately be linked to movements in economic output, consumption, and the business cycle.

We show that December to December industrial electricity growth, which is a purely quantity-based macroeconomic indictor, captures business cycle variations well. Its correlation with an annual NBER recession variable is 57 percent. While electricity usage data is observed with minimum delay, the NBER recession dates are often announced with significant lag, so industrial electricity growth captures the business cycle on a timelier basis. As a result, in our sampling period from 1961 to 2003, the industrial electricity growth does a good job of predicting future stock excess returns at both market and industry levels.[2] The in-sample R^2 is 9.7 percent when predicting next year market excess returns and is about 20 percent when predicting next year industry excess returns for several industries (such as nondurables and shops). When compared to a comprehensive list of predictive variables studied in Goyal and Welch (2008), our industrial electricity growth variable only underperforms the *cay* variable of Lettau and Ludvigson (2001) and the equity issuance variable (eqis) in terms of in-sample R^2. The predictive coefficient on our industrial electricity growth variable is negative and significant, consistent with a counter-cyclical market risk premium, as predicted by theoretical models such as Campbell and Cochrane (1999). Furthermore, the cross-industry variation in predictive power is consistent with the differential industry systematic risk exposures proxied using the Fama-French (1993) three-factor loadings.

The rest of the paper proceeds as follows. Section I describes the datasets used for this study and provides summary statistics of the main variables. Section II presents evidence supporting the standard CCAPM from the U.S. in time series and cross-sectional tests. Section III examines the calendar cycle effect on consumption in both the U.S. and European countries and tests an incomplete market model using state-level electricity consumption data. Section IV applies electricity data in return predictability tests. Section V provides concluding remarks.

[2] We end our sampling period at 2003 because of a change in the definition of user type in 2003 which makes industry electricity growth rate less comparable before and after 2002. If we ignore this "structure break" and extend our sampling period to 2008, we obtain very similar results. In fact, the relative performance of the industrial electricity growth rate actually improves.

I. Data

I. A. Data construction

This paper uses two main sets of data: various measures of consumption and stock return data. Monthly U.S. electricity consumption data are manually collected from two sources: *Electric Power Statistics* for 1960–1978 and *Electric Power Monthly* for 1979–2009. These documents are published each month by the Energy Information Administration (EIA) and report sales of electric energy (in millions of kilowatthours) to ultimate customers for residential customers, commercial customers, industrial customers, and other customers and total U.S. sales in each month.[3] As electricity consumption data could be revised later by the EIA, our hand collection of vintage data minimizes any potential forward-looking bias, which is an important concern when conducting return predictability tests. We also collect information on state-level (annual) electricity consumption from the EIA State Energy Data System from 1960 to 2009. Corresponding annual state population data are obtained from Surveillance Epidemiology and End Results (SEER) and U.S. Census Bureau population estimates.

In order to compare results from electricity consumption growth with those from other consumption measures, we use real per capita expenditure data from the National Income and Product Accounts (NIPA) of the Bureau of Economic Analysis. We add seasonally adjusted personal consumption expenditures of services and nondurable goods for 1960 to 2008. In addition, we obtain quarterly seasonally-unadjusted personal expenditure data for services and

[3] Based on the description of EIA Form 826, the residential sector consists of living quarters for private households. The commercial sector consists of service-providing facilities such as businesses, governments, and institutional living quarters. The industrial sector consists of facilities for producing goods, such as manufacturing (NAICS codes 31-33); agriculture, forestry, and hunting (NAICS code 11); mining, including oil and gas extraction (NAICS code 21); natural gas distribution (NAICS code 2212); and construction (NAICS code 23). Other customers include public street and highway lighting, public authorities, railroads and railways, and irrigation, as well as interdepartmental sales. Total electricity consumption accounts for the amount used by ultimate customers, and hence excludes resold or wasted amounts. It also excludes direct use, which is self-used, e.g., electricity used in power plants for generating electricity.

nondurable goods from Wayne Ferson's website. According to a study by Ferson and Harvey (1992), seasonally-unadjusted personal consumption expenditure data are considered to be a more accurate measure in terms of the timing of consumption. Annual garbage data from the U.S. Environmental Protection Agency (EPA) from 1960 to 2008 are kindly provided to us by Alexi Savov. As in Savov (2010), we exclude yard trimmings from total garbage generation.

We match these consumption data with U.S. stock returns and one-month Treasury bill returns, which we obtain from CRSP tape provided by Wharton Research Data Services for the 1960 to 2008 period. We match this data with the Fama and French 25 portfolios based on size and book-to-market, which are obtained from Kenneth French's website. We also obtain the consumption-wealth ratio ("cay") from Martin Lettau's website (Lettau and Ludvigson (2001)). Following Campbell (1999) and Savov (2010), we use the beginning-of-period time convention when matching return data to all year-on-year growth rates computed using *annual* data. For instance, the calendar year return in year t will be matched to the garbage growth computed using annual garbage generation in year t and t+1. For this reason, most of our time series tests stop at year 2008 and those involving garbage growth stop at year 2007.

The electricity consumption data for the European Union are provided by the European Network of Transmission System Operators for Electricity (ENTSO-E). Excluding the U.K., there are 10 countries that have reported their monthly electricity consumption through ENTSO-E since 1990. Of these countries, we include the eight for which we were able to find matching monthly stock return and risk-free rate data: Belgium, France, Germany, Italy, Netherlands, Portugal, Spain, and Switzerland. These monthly electricity consumption data are then merged with each country's stock market return and risk-free rate data from Datastream. In the U.K., electricity consumption is more extensively reported than in other EU countries. The National

Grid of the United Kingdom records daily electricity consumption data from 1971 to 2005, and half-hourly electricity consumption data from April 2001 to the present. To be consistent with the rest of the electricity data, we aggregate daily and half-hourly electricity consumption data at the monthly level from 1971 to 2008. This monthly U.K. electricity consumption data is merged with monthly U.K. stock market returns from Datastream over the same sampling period.

Finally, in our return predictability tests, we consider a comprehensive list of predictive variables studied in Goyal and Welch (2008). These variables at annual frequency are downloaded from Amit Goyal's website.

Using these consumption and stock market return data, we construct year-on-year consumption growth and market returns for each month. There are three main reasons for focusing on year-on-year monthly electricity consumption growth. First, the standard CCAPM requires seasonally-unadjusted spot consumption growth, which is best proxied by year-on-year monthly electricity growth (Breeden, Gibbons, and Litzenberger (1989)). Second, as in Jagannathan and Wang (2007), this focus allows us to examine the calendar effects of the CCAPM, where various discretionary consumption decisions are clustered within each month (e.g., holiday shopping, fiscal year-end tax decisions, realization of annual bonuses). Finally, electricity consumption data are exposed to strong within-year seasonal effects, such as weather fluctuations.

Figure 1 shows the normalized electricity demand for each month (Panel A) and the deviation of energy degree days in each month from its historical mean divided by its historical standard deviation (Panel B). As shown in the figure, average monthly variations in weather conditions and electricity demands within a year are positively correlated. This positive correlation is stronger for residential and commercial electricity usage.[4] Year-on-year electricity consumption growth identifies changes in consumption due to changes in economic conditions rather than seasonal weather effects. One may argue that year-on-year electricity consumption growth is still subject to residual weather effects (for instance, if February 2010 is unusually cold). Such extreme weather conditions are less likely to occur during months in the second and fourth quarters, such as April and December, which partly explains why April to April and December to December electricity consumption works better in Europe and the U.S., respectively. In addition, we work to eliminate extreme weather variations from year-on-year electricity consumption growth and focus on what remains. Unreported results suggest that residual electricity consumption growth (orthogonal to weather change) performs similarly in various CCAPM tests. In section III.B, we further confirm that repeating our tests in states with varying weather exposure generates very similar results. These results are intuitive: since stock market returns are unlikely to be driven by weather changes, the success of electricity growth in explaining stock market data is unlikely to be attributable to weather change.

I. B. Summary statistics

Table I shows the summary statistics for each component of electricity consumption. Per capita electricity consumption growth rates are measured year-on-year in December. As shown in the first row, three major components (residential, commercial, and industrial customers) are evenly represented in the data. Also, as shown in the second and third rows, electricity consumption growth is highly volatile, ranging from 3 to 6 percent, and well correlated with

[4] According to the 2007 10-K filing of Empire District Electric Co., "very hot summers and very cold winters increase electric demand, while mild weather reduces demand. Residential and commercial sales are impacted more by weather than industrial sales, which are mostly affected by business needs for electricity and by general economic conditions."

excess stock market returns. Prior literature (e.g., Savov (2010)) notes that high time series volatility contributes to reducing the relative risk aversion coefficient required in the time series tests of the CCAPM, and high correlation with the market contributes to a high consumption beta and significant pricing of consumption risk in the cross-section tests of the CCAPM.

Panel A of Table II shows the summary statistics of alternative consumption measures and their correlations. As shown in the first row, electricity usage is growing at an annual rate of about 2.5 percent, close to the growth rate of NIPA consumption data. However, as shown in the second row, the time series volatility differs among alternative consumption measures. Annual NIPA expenditure has the smallest volatility (1.294%), while December to December electricity consumption growth has the largest volatility (4.222%); this is likely to result in a smaller relative risk aversion coefficient estimate in the time series test of the CCAPM. The electricity growth rate computed using annual data has similar volatility to annual garbage growth (2.987% and 2.962%).

Based on Hall (1978), the ideal consumption stream should be martingale under the permanent income hypothesis. As shown in the third row, unlike measures based on NIPA seasonally-adjusted expenditures, December to December electricity consumption growth and garbage growth have a very small autocorrelation, which favorably reflects conditions implied under the permanent income hypothesis. Interestingly, electricity growth rates computed using annual data are much more autocorrelated, mainly due to the oil crisis in the early 1970s, which led to a permanent decrease in electricity growth rate.[5] The December to December electricity growth rate is less affected by this structural shift since the size of the shift is much smaller than the volatility of the December to December growth rate. Finally, the fourth row shows that

[5] If we remove the pre-crisis data or demean the structural shift, the autocorrelation decreases to 0.1.

electricity consumption growth is also highly correlated with excess market returns, comparable to alternative consumption measures.

Panel B of Table II shows correlations among alternative consumption measures. Unsurprisingly, the December to December electricity growth rate and the electricity growth rate computed using annual data are highly correlated (50.6%). In addition, December to December electricity consumption growth is also highly correlated with annual garbage growth (33.3%), annual personal consumption expenditure (35.4%), and with the Q4-Q4 measure (55.9%). Finally, when growth rates are all computed using annual data, expenditure growth is more correlated with electricity growth (67.5%) than with garbage growth (52.8%). These results are also confirmed in Figure 2, which shows that electricity consumption growth has the highest volatility of the alternative consumption measures and closely follows excess market returns as well as personal consumption expenditures. While factors such as supply-side shocks, technology innovations and regulatory changes could potentially impact electricity consumption growth at times, we do not find any significant change in the December to December electricity consumption in Figure 2 that would suggest a structural break. In unreported tests, we repeat the main analysis, excluding one year at a time. Our results do not appear to be driven by any particular year.

A unique feature of the electricity usage data allows us to break down the total usage by the types of end users (residential, commercial, and industrial). Panel C of Table II reports the correlations of alternative annual consumption growth measures with various electricity growth rates by end-user types. All growth rates are computed using annual data. In this panel, we consider data from 1960 through 2002 because of a change in the definition of user type in

2003.[6] We find that total electricity growth has high correlations (around 80 percent) with growth rates in all of its components. This is not surprising given that residential usage, commercial usage, and industrial usage contribute about equally to total electricity usage.

In sharp contrast, we find that garbage growth is highly correlated only with industrial electricity growth (72.8%), but not with residential or commercial electricity growth (12% and 22.3%). The difference in these correlations could be related to the fact that weather impacts residential, commercial, and industrial electricity usage differently (see Figure 1). However, the different correlations cannot be driven only by weather effect. When we look at NIPA expenditure growth in the last column, we again find it to correlate similarly with different components of electricity usage (44.5%, 57.1%, and 60.9% with residential, commercial, and industrial, accordingly).

The fact that garbage generation is only highly correlated with industrial electricity usage is consistent with the methodology the EPA uses to construct the garbage data. According to Savov (2010), "To collect this (garbage) data, the EPA uses what it calls a 'materials flow methodology'. Its numbers are based on both industry production estimates and waste site sampling. For example, to get a number for the amount of plastics waste generated in a given year, the EPA collects data on how much of various types of plastic products were produced that year and then estimates how much of that ended up discarded based on a complex calibration using data from landfills, recycling plants, and other sources." This leads to a natural concern that EPA garbage generation data may more directly proxy for production activity rather than the

[6] Previously, the EIA assigned electricity sales for public street highway lighting, other sales to public authorities, sales to railroads and railways, and interdepartmental sales to the "other customer" category. In 2003, the EIA revised its survey (Form 826) to separate transport-related electricity sales (the "Transport" category) and reassign the other activities to commercial and industrial sectors as appropriate. We confirm that correlations are similar even if we extend the sample period to 2008.

consumption of the representative agent.[7] To make sure that our electricity usage data do not suffer from a similar concern, we exclude industrial electricity usage from the total in several of our robustness checks and this exclusion hardly changes our results.

According to Ferson and Harvey (1992), seasonal adjustments introduce bias in the timing of consumption due to data smoothing using both past and future consumption data. Since electricity consumption is not seasonally adjusted, we expect it to correlate positively with seasonally-unadjusted NIPA expenditure growth. To account for seasonal effects, we compare quarter-to-quarter (e.g., Q1 to Q1) instead of quarterly growth (e.g., Q1 to Q2, Q2 to Q3, etc.). Table III shows correlations between quarter-to-quarter total electricity consumption growth, quarter-to-quarter seasonally-unadjusted NIPA expenditure growth (service and nondurable goods), and quarter-to-quarter seasonally-adjusted NIPA expenditure growth (service and nondurable goods). Indeed, the correlation between electricity consumption growth and seasonally-unadjusted expenditure growth is much higher than the correlations between seasonally-adjusted and unadjusted expenditure growths in each quarter. For example, in the third quarter, the former correlation is 18.4 percent, whereas the latter is only 2.2 percent. Also, electricity consumption growth highly correlates with seasonally-adjusted expenditure growths across all quarters in the range of 53 to 63 percent. Such a high correlation may suggest that electricity consumption correctly measures consumption over the life of a product, and, as a result, behaves more like the smoothed seasonally-adjusted consumption.

In the next three sections, we examine three asset pricing applications of the electricity usage data. We start by re-examining the performance of the standard CCAPM.

[7] Savov (2010) also examines an alternative garbage measure using numbers based entirely on waste site sampling, which are less likely to directly capture production activities. However, this alternative garbage measure only goes back to 1989.

II. The Standard CCAPM

II. A. The equity premium and risk-free rate: Evidence from time series tests

Table II shows that electricity consumption growth is volatile and positively correlated with market excess returns in the U.S. As a result, it might be able to justify the equity premium with a reasonable relative risk aversion parameter. We test it by estimating the following moment condition in GMM, which represents the Euler equation of a representative agent:

$$E_t\left[\beta\left(\frac{c_{t+1}}{c_t}\right)^{-\gamma} R^e_{t+1}\right] = 0, \tag{1}$$

where c_t is spot consumption, γ is the coefficient of relative risk aversion (RRA) and R^e_{t+1} is the annual excess return on the market or a portfolio (in excess of the T-bill return). β is the subjective discount factor and we set it to be 0.95, following Hansen and Singleton (1982) and Savov (2010), among others. Since the excess return is used in equation (1), β will not affect the estimation of γ.

Table IV shows our baseline results that use only one moment condition, as in Equation (1), with excess market return as the test asset and no other instruments.

Panel A shows the estimated relative risk aversion coefficient (RRA) for alternative measures of consumption. As shown in the panel, December to December electricity consumption growth yields a substantially lower RRA (17.3 with a standard error of 3.7). Electricity growth computed using annual data yields a slightly higher RRA (19.9 with a standard error of 11.9). These RRAs are much lower than the ones implied by consumption growth measures using NIPA expenditures. For example, the annual expenditure (Expenditure in column 4) yields an RRA of 42.7, and the Parker-Julliard (2005) ultimate consumption measure (PJ in column 7) yields an RRA of 83.1 with a non-zero pricing error. The fourth-quarter-to-fourth-quarter consumption measure proposed by Jagannathan and Wang (2007) (Q4–Q4 in column 5) yields an RRA of 40.8. When a December to December consumption measure is used (Dec-Dec in column 6), the RRA estimate becomes smaller (32.4) but still substantially higher than that from electricity consumption growth. The improvement from using electricity consumption growth is therefore not driven by the use of higher-frequency consumption data but rather indicates that electricity consumption is a better proxy of true spot consumption.

The only consumption measure that is comparable to electricity consumption growth is annual garbage growth, as in Savov (2010). However, the standard error of the RRA estimate is much smaller for December to December electricity consumption growth than for garbage growth, which suggests that a spot consumption growth measure may give more robust estimates.

High relative risk aversion implies a large risk-free rate due to increasing demand for precautionary savings (Weil, 1989). As a result, the higher γ associated with NIPA-expenditure-based consumption growth measures also implies unreasonably high risk-free rates of more than 80 percent per year. In contrast, December to December electricity consumption growth, as a better measure of consumption growth, only yields an implied risk-free rate of 17.5 percent, closer to its empirical counterpart.

In Panel B, we report RRA estimates for each component of electricity growth. In this panel, we again consider data from 1960 through 2002 because of a change in the definition of each sector in 2003. Since personal consumption is most likely to be reflected in electricity usage for individual households, we expect residential electricity consumption growth to give smaller RRA estimates than other electricity components. This is confirmed in the data; residential electricity consumption growth yields a smaller RRA (RRA=12.4) and a much smaller risk-free rate of 11.4 percent. We also note that industrial consumption growth yields a small RRA estimate (RRA=12.7), which is consistent with increased consumption activity related to increased production activity (i.e., firms produce more when people buy more). The lower RRA implied by industrial electricity growth and the fact garbage growth is highly correlated with only industrial electricity growth may partly explain why garbage growth also implies a lower RRA, as in Savov (2010). The concern, however, is that the industry component reflects production activity rather than the consumption of the representative agent. To show that industrial electricity usage is not driving our results, the fourth column shows the RRA estimate for the residential and commercial components only. The parameter estimate of RRA is 17.0, which is very close to that obtained using total electricity (RRA=16.5 for the same 1960–2002 period and 17.3 for the full 1960–2008 period).

Table V further explores implications of the CCAPM among different consumption measures using different assets and instruments.

Panel A reports results using excess market returns as the test asset and lagged consumption growth and lagged cay as instruments. For this specification, the RRA estimate from December to December electricity consumption growth leads to a slightly smaller RRA estimate (16.1) than that from garbage growth (16.6). Also, electricity consumption growth leads to a substantially smaller RRA estimate than all measures using NIPA-based personal consumption expenditures. Among those NIPA-based personal consumption measures, the quarterly spot consumption measure, Q4–Q4, performs best but still gives an RRA estimate of 39.3. Finally, annual electricity growth implies an even smaller RRA of 13.7.

Panel B shows results using excess returns on Fama and French 25 size and book-to-market portfolios as test assets. When December to December electricity consumption growth is used, the RRA estimate is 22.7 and the implied risk-free rate is a very reasonable 3.7 percent. Garbage growth implies a slightly smaller RRA of 21.7 but a larger implied risk-free rate of 10.8

percent. While larger than the RRA estimate obtained from a single moment condition, the December to December electricity consumption growth RRA estimate is much smaller than those obtained using other consumption measures. For example, the RRA estimate using annual personal consumption (”Expenditure”) is 62, and that using the Parker-Julliard consumption measure is 94.8. Both measures imply large risk-free rates exceeding 150 percent.

To sum up, RRA estimates from time series CCAPM suggest that spot consumption growth measured using December to December total electricity consumption growth performs substantially better than other NIPA-based consumption measures, and performs comparably to, if not slightly better than, garbage growth. In contrast to garbage growth, our results using electricity usage are less likely driven by production activities.

II. B. Evidence from the cross section

Another key insight of the CCAPM is that an asset's consumption beta – covariance between asset return and aggregate consumption growth – determines its expected return. This can be easily seen by linearizing the Euler equation of (1) as in Jagannathan and Wang (2007) and Savov (2010):

$$E[R_{t+1}^{e}] \approx \gamma \beta R^{f} Cov\left(\frac{c_{t+1}}{c_t}, R_{t+1}^{e}\right). \tag{2}$$

In this subsection, we test this cross-sectional implication of the CCAPM by running Fama-MacBeth (1973) regressions. Specifically, we first perform a time series regression on a portfolio's excess returns and various measures of consumption growth to obtain the consumption beta of that portfolio. We then run cross-sectional regressions of portfolio excess returns on their consumption betas. We choose the 25 Fama-French size and book-to-market portfolios which are the standard test assets for cross-sectional asset pricing. We first follow

Savov (2010) and omit the intercept terms in the cross-sectional regressions. According to Savov (2010), omitting the intercept imposes a restriction of the model and delivers more power. The results of these regressions are reported in Panel A of Table VI. In Panel B, we also report results after including intercept terms in the cross-sectional regressions which is a more standard procedure (see Lettau and Ludvigson (2001) and Jagannathan and Wang (2007), among many others).

For each regression specification, the regression coefficients are reported in the first row; Fama-MacBeth t-values with Newey-West (1987) correction are reported in the second row; t-values with both Shanken (1992) and Newey-West corrections are reported in the third row. The Shanken correction accounts for the estimation errors in betas from the time series regressions and the Newey-West correction accounts for autocorrelations in the errors with a lag of 3. The sampling period is again from 1961 to 2007.

The first two regressions in Panel A show that when there is no intercept term in the cross-sectional regression, both December to December electricity growth (eg) and the standard NIPA expenditure growth (cg) carry a significant positive consumption risk premium with similar pricing errors (3.05% and 3.07%, respectively). However, when we include both eg and cg in regression 3, we find eg to drive out cg, consistent with the notion that electricity growth might be better in capturing consumption risk than the expenditure growth.

In regression 4, we exclude industrial electricity usage and focus on only residential and commercial electricity when computing the December to December electricity growth rate (eg_rescom). We find eg_rescom to continue carrying a significant positive consumption risk premium, suggesting that the cross-sectional pricing power of electricity growth is not driven by its industrial component. The consumption risk premium remains significant in regression 5 when we compute the electricity growth rate using annual electricity usage (eg_A) although the pricing error becomes larger (3.74%).

We also confirm the result found by Savov (2010) that annual garbage growth (gg) carries a significant positive premium in regression 6. The pricing error associated with gg (3.33%) is higher than that associated with eg. When we put gg and eg together in regression 7, eg drives out gg, suggesting that December t o December electricity growth might be measuring consumption risk better than annual garbage growth.

For comparison purposes, in the last two regressions we also examine two alternative consumption risk measures that are documented to perform well in the cross-section. Indeed, Parker and Julliard's (2005) ultimate consumption risk measure (pj) and Jagannathan and Wang's (2007) year-on-year fourth quarter expenditure growth (cg_q4) are associated with the lowest pricing errors (2.56% for pj and 1.88% for cg_q4) and they both carry a significant consumption risk premium. When we compare the pricing errors across different regression specifications, the model that combines eg and cg generates the third lowest pricing error (2.62%).

Next, we repeat these regressions after adding the intercept terms and report the results in Panel B of Table VI. Interestingly, the significant positive consumption risk premium associated with December to December electricity growth (eg and eg_rescom) is robust to the inclusion of an intercept term in the cross-sectional regression (see regressions 1, 3, 4, and 7). In addition, the intercept terms are not statistically different from zero, further confirming the validity of the electricity-based CCAPM. In contrast, expenditure growth (cg) and garbage growth (gg) cease to have a significant risk premium once the intercept terms are included (see regressions 2 and 6). It remains true that December to December electricity growth better captures consumption risk than both NIPA expenditure growth and garbage growth (see regressions 3 and 7).

As a model misspecification test, we follow Jagannathan and Wang (2007) and estimate the Stochastic Discount Factor (SDF) representation of the CCAPM, CAPM, and Fama and French (1993) three-factor model given by:

$$E[(1 - b'f_{t+1})R^e_{t+1}] = 0, \tag{3}$$

where f denotes the December to December total electricity consumption growth (eg) or December to December electricity consumption growth for residential and commercial sectors (eg_rescom) in the case of the CCAPM, the market excess return (mktrf) in the case of the CAPM, and the three factors (mktrf, SMB, HML) in the case of the Fama and French three-factor model. The model is estimated by the generalized method of moments with the inverse of the second moments of asset excess returns as the weighting matrix. The results are presented in Panel C with the last column giving the Hansen and Jagannathan (1997, HJ) distance and the corresponding *p*-value. The HJ-distance is the smallest for the CCAPM when the consumption growth is measured using eg_rescom, providing fairly strong support for the CCAPM.

To summarize the results of the cross-sectional pricing tests, we find that December to December electricity growth is better than both NIPA expenditure growth and garbage growth in capturing consumption risk. The positive and significant consumption risk premium associated with December to December electricity growth is robust to the exclusion of industrial electricity usage, the inclusion of an intercept term in the cross-sectional regression, and the SDF estimation. The improvement in the CCAPM from the use of December to December electricity growth is consistent with monthly electricity usage being a better measure of spot consumption.

III. Additional Tests of Consumption-based Asset Pricing Models

III. A. Calendar cycle effect in consumption: U.S. and European evidence

In Table VII, we examine the year-on-year total electricity consumption growth over different calendar cycles in the context of the standard CCAPM. In Panel A, we report RRA estimates using year-on-year total electricity consumption growth for each month in the U.S. During the first four months of the year, the Euler equation in (1) does not hold on average and the resulting RRA estimates are not very meaningful. From May to December, the Euler equation holds and December to December electricity consumption growth yields the lowest RRA. The December to December RRA estimate is also associated with the smallest standard error.

There are at least two reasons why December to December electricity consumption growth might perform better in the CCAPM. First, as shown in row 5, electricity consumption is affected by weather conditions. Specifically, weather impacts are stronger in summer months due to increased cooling demand. Weather impact is measured by the correlation between monthly weather shock and total electricity consumption. Monthly weather shock is measured by the deviation of monthly energy degree days (EDD), which are in turn the sum of annual cooling degree days (CDD) and annual heating degree days (HDD). CDD (absolute value of temperature minus 65°F) and HDD (absolute value of 65°F minus temperature) are conventional measures of weather-driven electricity demand and are obtained from the National Oceanic and Atmospheric Administration (NOAA). During the three months from June to August, extreme weather variation drives year-on-year electricity consumption growth. In contrast, November and December year-on-year electricity consumption growth rates are much less affected by the weather change. As a result, December to December electricity consumption growth may be more informative about true spot consumption growth. Second, as argued in Jagannathan and Wang (2007), December, in the U.S., coincides with both the end of the tax year and the winter holiday. This is the time when investors both feel the need and have more leisure time to review their consumption and portfolio choice decisions, and consequently, the CCAPM should perform better.

We then examine a similar calendar cycle effect in European countries. This exercise also helps to further confirm the usefulness of total electricity consumption growth as a spot measure of consumption. We test the standard CCAPM in eight European countries using the 1990–2008 period due to the availability of electricity consumption data. In addition, we test the CCAPM in the U.K., where the available data period is longer; here we used the 1971–2008 period for our time series tests.

In these time series tests, we use excess market returns in each country as a test asset and estimate the relative risk aversion (RRA) coefficient in Equation (1) using the GMM. Panel B of Table VII shows parameter estimates from the time series tests of the CCAPM for the nine European countries in our sample. For most countries, the correlation between electricity consumption growth and excess market returns is high during March–June and November–December, and typically ranges from 20 to 50 percent. Also, the time series volatility of electricity consumption growth for these countries is very high, typically ranging from 3 to 6 percent. The estimates for relative risk aversion coefficients are moderate across most months (typically 5 – 30). In particular, April to April electricity growth consistently gives superior performance across all countries considered in our sample: the relative risk aversion required to justify the equity premium ranges from 5.6 in Belgium to 16.1 in Switzerland. In the U.K., where the time series is longer (1971–2008), the year-on-year electricity growth rate moves more closely with stock market returns only for the months from March to June and April to April electricity growth again yields the lowest RRA estimate (29.5) with zero pricing error. The RRA estimate of 29.5 is high relative to those from other European countries but is still much smaller than those documented in the prior literature using standard consumption data. For example, Campbell (2003) reports an RRA of 186 in the U.K. using data from 1970 to 1999 and 41.2 where the time series is longer; all RRA estimates are associated with zero pricing errors. According to Jagannathan and Wang (2007) and Jagannathan, Takehara, and Wang (2007), as investors feel the need and have more leisure time to review their consumption and portfolio choice decisions, the CCAPM should perform better. In Europe, the superior performance for April to April electricity consumption growth may be explained by the fact that April coincides with the end of the tax year in the U.K., and the Easter holiday throughout Europe.

Overall, time series evidence across the U.S. and nine European countries reveals an interesting calendar cycle effect, complementing the cross-sectional results in Jagannathan and Wang (2007) and Jagannathan, Takehara, and Wang (2007). The European evidence also provides additional out-of-sample support for our electricity-based CCAPM.

III. B. Incomplete market model: Evidence from state-level data

A popular alternative for explaining the equity risk premium puzzle is to relax the complete market assumption and allow heterogeneous agents to have uninsurable income shocks (see Constantinides and Duffie (1996) and Constantinides (2002), among many others). After relaxing the representative-agent assumption, the Euler equation (1) now holds for each consumer i, or:

$$E_t\left[\beta\left(\frac{c_{i,t+1}}{c_{i,t}}\right)^{-\gamma}R^e_{t+1}\right]=0. \tag{4}$$

Aggregating the Euler equations across N consumers in the economy, we have a new Euler equation:

$$E_t\left[\beta\frac{1}{N}\sum_{i=1}^{N}\left(\frac{c_{i,t+1}}{c_{i,t}}\right)^{-\gamma}R^e_{t+1}\right]=0, \tag{5}$$

Following Jacobs, Pallage, and Robe (2005) and Korniotis (2008), we test equation (4) not using data on individual consumption, but data on state consumption. State-level consumption data alleviates measurement error associated with individual consumption data sets such as the Consumer Expenditure Survey and the Panel Study of Income Dynamics. In addition, it can be interpreted as a proxy for the consumption of a synthetic cohort as studied by Browning, Deaton, and Irish (1985) and Attanasio and Weber (1995). Jacobs, Pallage, and Robe (2005) and Korniotis (2008) measure annual state-level consumption with retail sales data. In contrast, we measure annual state-level consumption with total electricity usage. In other words, c_i in equation (3) is measured using per capita annual electricity usage in state i. When we aggregate across states, we consider both the equally-weighted average as in equation (4) and the population-weighted average. We use annual state electricity usage as the data go back to 1960 while monthly state-level electricity usage data only become available in 1990.

Summary statistics of annual state-level electricity growth rates and GMM test results of equation (4) are reported in Table VIII. We find that state-level electricity growth rates correlate well with market excess returns (with average correlations of around 24%) and are highly volatile (with an average standard deviation of more than 4%). State-level electricity consumption growth yields an RRA of 18.4 with a standard error of 7.4 using equal-weighting in equation (4). The implied risk-free rate is 13.9 percent. Weighting state-level Euler equations using population does not change the result much. Interestingly, the required RRA of around 18 is very close to the estimate in Jacobs, Pallage, and Robe (2005) where state-level consumption is measured using retail sales data, confirming that electricity usage is a good proxy for consumption even at the state level. In addition, the required RRA of around 18 using state-level electricity usage data is only slightly smaller than the estimate using aggregate U.S. annual electricity usage (19.9 as reported in Panel A of Table IV). One interpretation of this is that when consumption is measured more accurately using electricity consumption, then relaxing the complete market assumption does not significantly improve the performance of the CCAPM.

An alternative explanation is that state-level electricity consumption growth is more likely to be affected by weather fluctuation. Moving from aggregate U.S. electricity consumption to state-level electricity consumption may introduce additional "noise" and thus will not improve the performance of the CCAPM significantly. If this explanation is correct and weather fluctuation indeed drives electricity growth, we would expect a state with more weather fluctuation to have more volatile electricity growth as well. This does not seem to be the case, as is evident in Figure 3, where we present the distribution of annual historical energy degree day (EDD) volatility (upper plot) and annual electricity consumption growth volatility (lower plot). Recall that EDD, being a sum of CDD (absolute value of temperature minus 65^{o}F) and HDD (absolute value of 65^{o}F minus temperature), is a conventional measure of weather-driven electricity demand. The upper plot displays the expected pattern that northern states in U.S. are associated with more severe weather fluctuations from one year to the other than the southern states. In contrast, the lower plot shows no clear pattern about the distribution of electricity consumption growth volatility. Overall, while weather fluctuation is positively correlated with electricity growth volatility across states (the correlation is about 10%), electricity growth does not seem to be driven by weather fluctuation.

More importantly, we directly test the impact of weather fluctuation on our time series tests and report the results in Panel B of Table VIII. We classify 48 states with non-missing EDD measures into two groups according to their annual EDD volatility.[8] As seen from Figure 3, the 24 states in the high EDD volatility group are mainly the northern states while the 24 states in the low EDD volatility group are mainly the southern states. We then test the main Euler equation at both aggregate level (equation 1) and at the state level (equation 4 with population-weighting) within each of the two groups. The results in the two groups turn out to be very similar, confirming that weather fluctuation has little impact on the asset pricing results in this paper.

IV. Stock Return Predictability

Preceding sections consider electricity consumption growth as a measure of consumption risk of a representative investor. In the U.S., electricity consumption data are available across three broad sectors of the economy: households (residential electricity usage), commercial businesses (commercial electricity usage), and industrial firms (industrial electricity usage). While residential and commercial electricity usage has been shown to be a good measure of the representative agent's consumption, in this section, we explore the possibility of using industrial electricity usage as an economic indicator that forecasts future stock returns.

Since factories typically use electricity in their production and electricity cannot be stored, industrial electricity usage is likely to track production and economic output and thus business cycle fluctuation in real time. In Panel A of Table IX, we report the simple correlations between various consumption risk variables and an annual NBER business cycle variable defined as the

[8] The two states with missing EDD data are Alaska and Hawaii. Washington, D.C. also has missing EDD data.

fraction of each year spent in non-recession. As shown in the table, December to December industrial electricity consumption growth has the highest correlation (57%). The only other growth variable that has comparable correlation (55%) with the NBER business cycle variable is Q4-Q4 NIPA consumption growth as in Jagannathan and Wang (2007).

It is important to highlight that the NBER recession dates are often announced with significant delay. Industrial electricity usage, available with minimum delay, could capture business cycles on a more timely basis. If the market risk premium is countercyclical, as predicted by theoretical models such as Campbell and Cochrane (1999), then our industrial electricity growth rate could be a good predictor of future stock excess returns. We test this conjecture using time series regressions following the standard procedures in the return predictability literature (see Goyal and Welch (2008) for a comprehensive study of return predictability). Specifically, we consider the following univariate predictive regression:

$$R_{t+1}^{e} = \alpha + \beta X_t + \varepsilon_{t+1}, \tag{6}$$

where R_{t+1}^{e} is the next year excess stock returns, X_t is the current year predictive variable, and ε_t is random noise. For excess returns, we consider the CRSP value-weighted market returns over T-bill rates and Fama-French 12 industry returns over T-bill rates. Predictive variables are December to December growth rate in components of electricity usage (residential, commercial, industrial, and total), book-to-market ratio (b/m), investment to capital ratio (i/k), net equity expansion (ntis), percent equity issuing (eqis), consumption wealth ratio (cay), dividend yield (dy), earnings price ratio (ep), the annual garbage growth rate as in Savov (2010) (gg), and year-on-year fourth quarter expenditure growth as in Jagannathan and Wang (2007) (cg_q4). We choose to include b/m, i/k, ntis, eqis, cay, dy, and ep since Goyal and Welch (2008) find them to have significant predictive power among a comprehensive list of predictive variables they studied. We compute bootstrap *p*-values associated with the regression estimates following the procedure detailed in Goyal and Welch (2008). These bootstrap *p*-values account for the persistence in the predictor, cross-correlation in the error terms and the small-sample problem. We examine predictive variables in the sample period, 1960–2002, due to the change in the definition of electricity usage sectors in 2003. If we ignore this "structure break" and extend our sampling period to 2008, unreported results suggest our industrial electricity growth perform even better. Given the relatively short sampling period, we do not compute the out-of-sample R^2.

In Panel B, Table IX, we report results from the predictive regressions for next year excess market returns. As shown in Panel B, the parameter estimate on December to December industrial electricity consumption growth is significantly negative. That is, lower industrial electricity growth in the current period forecasts higher excess returns over the following year, consistent with a countercyclical premium so the market risk premium increases during an economic downturn. The R^2 for this regression is 9.68% which is also highly significant. Among other variables considered in Goyal and Welch (2008), only percent equity issuing (eqis) and the consumption-wealth ratio (cay) have higher R^2 (10.66% and 22.82%). While eqis and cay are both computed using price information and cay is also calculated via forward-looking full sample estimation, our industrial electricity growth variable is purely quantity-based and does not require any full-sample estimation.

Panel B also shows that another consumption growth measure (cg_q4) does a reasonably good job of predicting next year market excess returns (albeit not as good as our industrial electricity growth in the sampling period 1960-2002). The relatively superior performance of cg_q4 in predicting future market excess returns confirms the recent findings by Moller and

Rangvid (2010) and is consistent with the high correlation between cg_q4 and the NBER business cycle variable documented in Panel A.

In Panel C, Table IX, we further examine industry-level predictability using Fama-French 12 industry portfolios. To save space, we only consider the top three predictive variables: industrial electricity growth, eqis, and cay. Among 12 industries, the nondurable (R^2=19.2%), durable (R^2=17.5%), manufacturing (R^2=14.3%), chemical (R^2=17.9%), shops (R^2=20.5%), and money (R^2=17.1%) industry excess returns are well predicted by industrial electricity consumption growth with significant parameter estimates and high R^2. Using eqis and cay, we find similar predictability patterns; excess returns in the nondurable, durable, manufacturing, chemical, shops, and money industries are well predicted. In terms of predictability R^2, industrial electricity consumption growth has better predictive power than percent equity issuing (eqis) for most industries, and has similar predictive power to the consumption-wealth ratio (cay).

If the countercyclical market risk premium is behind the predictive relation between current industrial electricity consumption growth and future stock excess returns, we would expect strong predictive power among industries with higher exposures to systematic risk (see Rapach, Strauss, Tu, and Zhou (2010) for a similar argument). Figure 4 provides consistent evidence supporting this conjecture. We plot the R^2 from the predictive regressions (using industrial electricity growth) across the 12 industries against each of the three factor betas (MKTRF betas in panel (a), SMB betas in panel (b) and HML betas in panel (c)). As shown in these figures, predictive R^2s are indeed positively correlated with all three betas.

While a more extensive investigation of the predictive power of electricity consumption growth warrants a separate study, the results in this section do suggest that electricity consumption growth is a useful economic indicator in forecasting future asset returns.

V. Conclusions

In this paper, we propose electricity consumption growth as a new real-time measure of economic activities such as aggregate spot consumption and business cycle fluctuations. This is because most modern-day economic activities involve the use of electricity, which cannot be easily stored. The availability of high frequency data at both aggregate and disaggregate levels permits us to examine the link between economic activities and asset prices. We find that electricity usage can better explain stock returns in both time series and cross-section within the consumption-based asset pricing framework. It is also capable of capturing business cycle fluctuations and predicts future stock excess returns well.

In the U.S. from 1961 to 2008, electricity consumption growth is able to match the equity premium with a relative risk aversion of 17.3, which is much lower than those associated with the NIPA expenditure growth measures. In the cross section, we find a positive and significant consumption risk premium using December to December annual electricity growth rates. In addition, our results are not driven by electricity demand coming from production activities and extreme weather fluctuations.

Electricity usage data is available at a disaggregated level, at higher frequency, and almost in real time, which allows us to study additional implications of consumption in asset pricing. We examine two such implications in our paper. We test the calendar effect associated with aggregate consumption using monthly electricity data and we test the CCAPM with incomplete market and uninsurable income shocks using state-level electricity data.

Finally, we show that December to December industrial electricity growth captures business cycle variations well and has a high correlation (57%) with an annual NBER business cycle variable. This property leads to good performance in predicting future stock excess returns at both market and industry levels with an in-sample R^2 of 9.7 percent for future excess market returns and of 20 percent for industry excess returns for several industries (such as consumer, nondurables, and shops).

Beyond establishing a strong link between fundamental economic activities and asset prices, our paper also illustrates the usefulness of electricity consumption data in financial applications. High-frequency real time electricity usage data points to further applications in areas where accurate timing is an important issue. We leave them for future studies.

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TABLE I. SUMMARY STATISTICS: COMPONENTS OF ELECTRICITY CONSUMPTION GROWTH

Information on monthly sales of electric energy to ultimate customers is collected from the Energy Information Administration's (EIA) *Electric Power Statistics* (1960–1978) and *Electric Power Monthly* (1979–2008). Electricity growth is measured by year-on-year December electricity consumption growth by sector. Sector-level results consider 1960–2002 data due to a change in the definition of each sector in 2003. According to EIA Form 826, residential sector consists of living quarters for private households. Commercial sector consists of service-providing facilities and equipment of business; Federal, state, and local governments; and other private and public organizations, such as religious, social, or fraternal groups. Industrial sector consists of all facilities and equipment used for producing, processing or assembling goods. The following types of activities are included in the industrial sector: manufacturing (NAICS codes 31-33); agriculture, forestry, and hunting (NAICS code 11); mining, including oil and gas extraction (NAICS code 21); natural gas distribution (NAICS code 2212); and construction (NAICS code 23). Aside from residential, commercial, and industrial sectors, other electricity consumption activities such as public street and highway lighting, other sales to public authorities, sales to railroads and railways, sales for irrigation, and interdepartmental sales are also included in the total electricity consumption. In the fourth row, excess market returns are measured by value weighted U.S. stock returns over one-month Treasury bill returns.

	Residential	Commercial	Industrial	Res & Com	Total
Proportion (%)	33.5	25.1	37.9	58.6	100.0
Mean	1.034	1.041	1.017	1.048	1.029
Std. dev. (%)	5.9	3.4	6.0	4.6	4.4
Corr. with R_m (%)	10.2	23.6	33.3	16.7	27.3

TABLE II. CORRELATIONS BETWEEN ALTERNATIVE MEASURES OF CONSUMPTION

Electricity growth is December to December (Column 1) and annual (Column 2) total electricity consumption growth and is based on total electricity consumption data obtained from the Energy Information Administration (EIA). Garbage is the annual growth rate of municipal solid waste (MSW) provided by Environmental Protection Agency (EPA). Expenditure is the annual growth rate of National Income Product Account's seasonally-adjusted annual services and nondurable goods. P-J is the ultimate consumption growth by Parker and Julliard (2005). Q4-Q4 is the year-on-year fourth quarter expenditure growth by Jagannathan and Wang (2007). Excess market returns are measured by value weighted U.S. stock returns over one-month Treasury bill returns. Panel A provides summary statistics for alternative consumption risk measures for 1961-2008, except for garbage (1961-2007) and P-J (1961-2006). Panel B shows correlations among alternative consumption risk measures. Panel C shows correlations of alternative annual consumption risk measures with individual components of electricity consumption growth.

Panel A. Summary statistics

	Electricity (Dec-Dec)	Electricity (annual)	Garbage	Expenditure	P-J	Q4-Q4
Mean	1.025	1.023	1.014	1.021	1.066	1.022
Std. dev.	4.222	2.987	2.963	1.294	3.013	1.391
Autocorrelation (%)	-11.227	57.626	-12.052	47.319	75.975	34.523
Corr. with R_m (%)	26.105	38.312	55.866	45.653	0.995	41.061

Panel B. Correlations (%)

	Electricity (Dec-Dec)	Electricity (annual)	Garbage	Expenditure	P-J
Electricity (annual)	50.6				
Garbage	33.3	51.0			
Expenditure	35.4	67.5	52.8		
P-J	17.9	38.2	10.5	45.2	
Q4-Q4	55.5	60.4	52.1	62.2	5.8

Panel C. Correlations with components of electricity growth (%)

Electricity (by sector)	Electricity	Garbage	Expenditure
Residential	81.7	12.0	44.5
Commercial	76.5	22.3	57.1
Industrial	83.4	72.8	60.9
Res. & Com.	84.9	17.0	52.8
All	100.0	52.5	67.5

TABLE III. CORRELATIONS BETWEEN ELECTRICITY CONSUMPTION AND SEASONALLY ADJUSTED/UNADJUSTED CONSUMPTION GROWTH

"eg" (electricity growth) is based on total electricity consumption data obtained from the Energy Information Administration. "cag" is seasonally-adjusted year-on-year quarterly expenditure growth by Jagannathan and Wang (2007). Personal consumption expenditure is National Income Product Account's seasonally-adjusted annual services and nondurable goods. "cug" is seasonally-unadjusted year-on-year quarterly expenditure growth by Ferson and Harvey (1992). Seasonally-unadjusted consumption is available until 2001.

	Q1			Q2			Q3			Q4		
	eg	cug	cag	eg	cug	cag	eg	cug	cag	eg	cug	cag
eg	100.0	6.9	55.0	100.0	6.5	59.0	100.0	18.4	58.4	100.0	13.9	63.5
cug	6.9	100.0	-6.8	6.5	100.0	0.4	18.4	100.0	2.2	13.9	100.0	9.6
cag	55.0	-6.8	100.0	59.0	0.4	100.0	58.4	2.2	100.0	63.5	9.6	100.0

TABLE IV. THE EQUITY PREMIUM: TIME SERIES EVIDENCE FROM THE U.S. STOCK MARKET (BASELINE)

Electricity growth is December to December (Column 1) and annual (Column 2) total electricity consumption growth and is based on total electricity consumption data obtained from the Energy Information Administration (EIA). Garbage is the annual growth rate of municipal solid waste (MSW) provided by Environmental Protection Agency (EPA). Expenditure is annual growth rate of National Income Product Account's seasonally-adjusted annual services and nondurable goods. P-J is the ultimate consumption growth by Parker and Julliard (2005). Q4-Q4 is the year-on-year fourth quarter expenditure growth by Jagannathan and Wang (2007). Dec-Dec is the year-on-year December (seasonally adjusted) expenditure growth. Following Campbell (1999) and Savov (2010), we use the beginning-of-period time convention when matching return data to all year-on-year growth rates computed using *annual* data. For instance, the calendar year return in year t will be matched to the garbage growth computed using annual garbage generation in year t and t+1. Panel A shows parameter estimates of CCAPM, Equation (1), for alternative measures of consumption risk. RRA is the relative risk aversion constant. Implied R_f is based on estimated RRA. Sample periods are from 1961 to 2008 except for garbage (1961-2007) and P-J (1961-2006). Panel B shows parameter estimates of CCAPM, Equation (1), for individual components of electricity consumption growth. Results in Panel B consider 1960–2002 data due to a change in the definition of each sector in 2003.

Panel A. Alternative measures of consumption growth

	Electricity (Dec-Dec)	Electricity (annual)	Garbage	Expenditure (annual)	Expenditure (Q4-Q4)	Expenditure (Dec-Dec)	P-J
RRA	17.3	19.9	17.5	42.7	40.8	32.4	83.1
RRA(s.e.)	3.7	11.9	8.5	23.8	25.1	18.2	-
Implied R_f (%)	17.5	40.0	14.4	119.4	113.2	86.8	1190.5
Pricing error	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.6668

Panel B. Components of electricity consumption growth (Dec-Dec)

	Residential	Commercial	Industrial	Res. & Com.	Total
RRA	12.4	31.5	12.7	17.0	16.5
RRA(s.e.)	3.2	9.9	3.9	4.3	3.9
Implied R_f (%)	11.4	122.5	-6.1	63.6	21.0
Pricing error	0.0000	0.0000	0.0000	0.0000	0.0000

TABLE V. THE EQUITY PREMIUM: TIME SERIES EVIDENCE FROM THE U.S. STOCK MARKET (WITH INSTRUMENTS AND MULTIPLE ASSETS)

Electricity growth is December to December (Column 1) and annual (Column 2) total electricity consumption growth and is based on total electricity consumption data obtained from the Energy Information Administration (EIA). Garbage is the annual growth rate of municipal solid waste (MSW) provided by Environmental Protection Agency (EPA). Expenditure is annual growth rate of National Income Product Account's seasonally-adjusted annual services and nondurable goods. P-J is the ultimate consumption growth by Parker and Julliard (2005). Q4-Q4 is the year-on-year fourth quarter expenditure growth by Jagannathan and Wang (2007). Dec-Dec is the year-on-year December (seasonally adjusted) expenditure growth. Sample periods are from 1961 to 2008 except for garbage (1961-2007) and P-J (1961-2006). Panel A shows parameter estimates of CCAPM with lagged cay and lagged consumption growth as instruments. Panel B shows parameter estimates of CCAPM with Fama-French 25 size and market-to-book portfolios as test assets.

Panel A. Market return with instruments (lagged cay and lagged consumption growth)

	Electricity (Dec-Dec)	Electricity (annual)	Garbage	Expenditure	P-J	Q4-Q4
RRA	16.1	13.7	16.6	57.2	98.0	39.3
RRA(s.e.)	3.0	8.4	7.7	20.9	17.3	25.2
Implied rf (%)	18.0	31.6	14.4	158.8	1214.5	108.0
Pricing error	2.7768	3.2020	2.3417	3.1079	2.2506	3.6100

Panel B. 25 Fama-French size and market-to-book portfolios with no instruments

	Electricity (Dec-Dec)	Electricity (annual)	Garbage	Expenditure	P-J	Q4-Q4
RRA	22.7	27.4	21.7	62.0	94.8	61.2
RRA(s.e.)	1.4	3.0	1.9	6.0	2.7	4.8
Implied rf (%)	3.7	42.7	10.8	174.5	1238.8	168.7
Pricing error	5.0942	5.0402	5.0856	4.8995	4.0006	4.9914

TABLE VI. CROSS-SECTIONAL EVIDENCE FROM THE U.S. STOCK MARKET: FAMA-MACBETH REGRESSIONS

eg is December to December total electricity growth. eg_rescom is December-to-December growth in residential and commercial electricity consumption. eg_A is the electricity growth rate using total annual electricity consumption. gg is annual garbage growth rate by Savov (2010). pj is the ultimate consumption growth by Parker and Julliard (2005). cg_q4 is the year-on-year fourth quarter expenditure growth by Jagannathan and Wang (2007). For each regression specification in Panel A and B, the regression coefficients are reported in the first row, Fama-MacBeth t-values with Newey-West correction are reported in the second row, t-values with both Shanken and Newey-West corrections are reported in the third row, and the root-mean-square pricing errors (RMSE) are reported in the last column. The Shanken correction accounts for estimation errors in betas from the time-series regressions. The Newey-West correction accounts for autocorrelations in the errors with a lag of 3. In Panel A, we report results of cross-sectional regressions without intercept terms, and Panel B with intercept terms. In Panel C, we estimate the stochastic discount factor model, $E[(1-b'f_{t+1})R_{t+1}^{e}]=0$, using the GMM and report parameter estimate and t-statistics. The last column gives the HJ distance and the corresponding p-value.

Panel A: Cross-sectional regressions with no intercept terms

eg	cg	eg_rescom	eg_A	gg	pj	cg_q4	rmse
0.085							0.0305
4.361							
2.026							
	0.014						0.0307
	4.057						
	2.290						
0.053	0.012						0.0262
3.569	2.917						
2.307	1.894						
		0.090					0.0319
		4.097					
		2.021					
			0.029				0.0374
			3.263				
			2.388				
				0.026			0.0333
				4.056			
				2.135			
0.058				0.023			0.0286
3.793				3.243			
2.146				1.813			
					0.306		0.0256
					3.538		
					2.108		
						0.020	0.0188
						4.329	
						1.954	

TABLE VI (CONTINUED)

Panel B: Cross-sectional regressions with intercept terms

inter	eg	cg	eg_rescom	eg_A	gg	pj	cg_q4	rmse
0.039	0.052							0.0291
1.351	3.167							
0.886	2.060							
0.044		0.008						0.0282
1.465		1.413						
1.481		1.345						
0.007	0.049	0.011						0.0262
0.205	3.066	1.945						
0.186	1.962	1.713						
0.046			0.047					0.0286
1.567			2.968					
1.070			1.946					
0.082				0.007				0.0316
3.468				0.511				
3.474				0.528				
0.061					0.010			0.0315
1.174					0.574			
1.260					0.562			
0.007	0.055				0.021			0.0286
0.133	2.999				1.167			
0.128	2.108				0.968			
0.010						0.271		0.0254
0.401						2.806		
0.286						2.364		
-0.025							0.025	0.0180
-0.725							3.258	
-0.364							1.712	

TABLE VI (CONTINUED)

Panel C: GMM estimation

eg	eg_rescom	mktrf	smb	hml	HJ dist/*p*-val
13.13					0.64
5.77					0.27
	12.68				0.53
	10.57				0.37
		2.22			0.73
		2.85			0.18
		2.52	0.22	3.32	0.57
		3.66	0.25	4.36	0.26

TABLE VII. THE EQUITY PREMIUM: TIME SERIES EVIDENCE FROM THE U.S. AND EUROPEAN COUNTRIES OVER DIFFERENT CALENDAR CYCLES

Electricity growth is based on total electricity consumption data. For U.S. it is obtained from the Energy Information Administration (EIA, 1961-2008). For European countries, it is obtained from the World Bank (1991–2008), except for the United Kingdom, where it is obtained from the National Grid (1972–2008). Stock excess return data in European countries is obtained from Datastream. Correlation with Rm is the correlation between electricity consumption growth and excess market return. Std. Dev. is the standard deviation of consumption growth time-series. RRA is the relative risk aversion constant. Implied R_f is based on estimated RRA. In Panel A where we report the U.S. evidence, we also report weather correlation defined as the correlation between month-to-month weather shock and total electricity consumption. The monthly weather shock is measured by the deviation of monthly energy degree days from the historical mean divided by the historical standard deviation. Energy degree days (EDD) is the sum of annual cooling degree days (CDD) and annual heating degree days (HDD). CDD and HDD are obtained from the National Oceanic and Atmospheric Administration.

Panel A: U.S. evidence

	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
RRA	16.8	6.7	9.2	14.9	61.3	31.7	23.3	43.7	25.6	23.2	27.8	17.3
RRA(s.e.)	–	–	–	–	29.3	13.2	10.0	24.9	12.6	12.8	14.8	3.7
Implied R_f (%)	21.3	19.3	24.3	33.1	-22.4	10.4	29.7	-30.0	12.2	22.7	35.2	17.5
Pricing error	2.0849	2.9324	2.9884	2.8587	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Weather corr.	-27.4	-23.0	-23.0	-27.5	-15.2	38.2	43.0	46.5	-11.4	13.9	-0.9	-8.3

Panel B: European evidence

	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Belgium												
Corr. R_m (%)	-3.9	19.5	35.5	40.4	37.8	41.1	26.6	24.6	12.6	11.3	53.2	49.8
Std.dev (%)	3.6	4.5	4.5	5.0	3.9	3.3	3.6	3.2	2.7	3.2	3.0	3.2
RRA	37.5	9.1	7.4	5.7	8.5	10.9	15.0	20.6	22.9	20.3	12.4	11.1
RRA (s.e.)	46.1	10.0	8.6	5.6	8.0	10.3	10.8	17.7	–	–	5.9	6.8
Pricing error	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.4161	1.3454	0.0000	0.0000
France												
Corr. R_m (%)	-9.9	-15.0	25.7	22.6	31.9	2.0	-13.0	24.1	-3.5	0.9	26.6	5.1
Std.dev (%)	5.5	7.0	6.9	6.0	2.8	1.8	1.7	2.3	3.1	5.4	6.7	5.3
RRA	0.2	-21.8	5.9	10.9	49.3	65.9	105.2	98.8	57.4	2.3	17.8	29.2
RRA (s.e.)	–	–	–	7.1	101.8	42.5	66.1	117.2	10.7	–	8.1	15.8
Pricing error	0.9228	0.0038	0.4406	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.2209	0.0000	0.0000

TABLE VII (CONTINUED)

	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Germany												
Corr. R_m (%)	2.3	5.3	32.0	29.3	38.6	39.1	28.7	25.4	0.3	1.7	15.7	2.6
Std.dev (%)	5.8	8.3	5.7	6.4	5.3	4.7	5.8	5.4	4.8	4.3	5.8	5.6
RRA	1.7	17.8	17.3	7.2	9.2	10.0	10.1	12.3	4.9	3.7	18.9	6.5
RRA (s.e.)	–	23.4	–	6.6	7.8	9.2	6.3	11.6	–	–	–	–
Pricing error	0.7684	0.0000	0.0314	0.0000	0.0000	0.0000	0.0000	0.0000	1.1310	1.1080	0.4410	1.2150
Italy												
Corr. R_m (%)	42.2	41.1	37.8	19.4	44.6	38.7	29.2	28.6	37.1	27.8	48.6	63.4
Std.dev (%)	3.7	4.2	3.6	3.8	2.8	3.4	3.3	3.5	3.4	2.4	2.8	3.1
RRA	6.1	3.4	6.9	7.4	7.2	6.7	11.4	14.2	21.9	36.2	12.6	9.8
RRA (s.e.)	9.9	9.0	12.5	9.9	11.9	11.7	12.5	11.1	13.3	–	12.0	7.1
Pricing error	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0355	0.0000	0.0000
Netherlands												
Corr. R_m (%)	-2.6	11.1	38.0	43.0	50.9	44.1	36.2	37.2	19.2	-8.0	-6.0	-2.9
Std.dev (%)	3.9	3.9	4.1	3.4	3.4	3.0	3.4	4.0	3.4	4.4	3.6	3.9
RRA	29.7	40.4	10.6	11.4	12.0	16.3	17.5	14.6	35.0	1.8	5.2	4.7
RRA (s.e.)	27.6	96.0	12.3	11.2	11.2	15.4	15.9	11.7	12.6	–	–	–
Pricing error	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.3397	1.6831	1.8679
Portugal												
Corr. R_m (%)	-9.8	-0.2	4.3	26.8	29.4	11.9	-3.8	10.9	27.5	-10.2	-10.8	5.3
Std.dev (%)	3.8	5.8	5.9	3.5	3.1	2.9	3.1	3.7	2.9	3.1	3.3	3.9
RRA	63.5	5.7	22.6	13.1	15.3	84.6	40.9	54.0	40.3	21.4	8.9	28.3
RRA (s.e.)	48.9	–	49.4	12.3	14.9	61.9	17.7	–	–	–	–	13.3
Pricing error	0.0000	0.3241	0.0000	0.0000	0.0000	0.0000	0.0000	0.6630	1.1406	1.7363	1.7040	0.0000

TABLE VII (CONTINUED)

	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Spain												
Corr. R_m (%)	15.3	19.7	26.5	46.8	39.0	23.3	13.2	11.2	30.0	22.5	30.1	18.2
Std.dev (%)	3.8	5.8	5.2	5.4	3.5	3.3	3.5	3.7	3.6	3.2	4.9	5.5
RRA	22.8	27.2	18.0	8.1	13.7	25.5	125.9	178.5	16.2	29.6	26.5	9.0
RRA (s.e.)	12.0	–	25.7	5.8	9.8	16.1	91.5	215.3	–	–	–	–
Pricing error	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.5792	0.7396	0.1828	1.3280
Switzerland												
Corr. R_m (%)	-40.8	-19.6	1.2	10.1	30.4	13.8	7.5	11.2	-21.6	6.3	36.7	4.5
Std.dev (%)	3.6	5.6	4.4	4.9	3.1	2.5	2.2	1.8	2.4	2.6	3.7	3.3
RRA	-31.9	-6.1	3.2	16.1	31.3	44.9	79.4	36.7	4.8	16.1	40.3	17.0
RRA (s.e.)	11.7	–	–	8.2	28.0	33.6	49.3	–	–	–	17.8	–
Pricing error	0.0000	0.9067	1.1163	0.0000	0.0000	0.0000	0.0000	1.1436	1.5010	1.5145	0.0000	1.3148
U.K.												
Corr. R_m (%)	-4.4	0.5	18.8	15.7	24.3	29.8	-0.7	-6.7	-24.8	-40.0	-22.7	-1.6
Std.dev (%)	5.8	7.0	4.9	5.1	4.0	3.0	2.9	3.2	2.9	3.9	3.8	3.8
RRA	13.0	13.5	16.6	29.5	30.9	23.9	7.8	2.2	-6.1	-26.8	-8.6	5.0
RRA (s.e.)	5.3	6.9	–	19.7	12.3	–	–	–	–	15.5	–	–
Pricing error	0.0000	0.0000	1.1242	0.0000	0.0000	1.9909	2.3850	2.3745	1.8997	0.0000	1.9316	1.7368

TABLE VIII. TESTS FOR CCAPM WITH HETEROGENEOUS AGENTS USING U.S. STATE-LEVEL ELECTRICITY CONSUMPTION DATA

Electricity growth is annual total electricity consumption growth and is based on total electricity consumption data obtained from the EIA State Energy Data System. State-level electricity consumption data is divided by state population to obtain per capita electricity consumption in each state. Annual state population is obtained from Surveillance Epidemiology and End Results (SEER) from 1969 to 2007, and from U.S. Census Bureau population estimates from 2008 to 2009. RRA is the relative risk aversion constant. Implied R_f is based on estimated RRA. Panel A shows parameter estimates of heterogeneous agent for all 51 states (including Washington DC) in the United States. Panel B shows CCAPM estimates for low EDD-volatility and high EDD-volatility samples. Historical weather volatility is measured by the standard deviation of EDD from 1960-2008. Energy degree days (EDD) is the sum of annual cooling degree days (CDD) and annual heating degree days (HDD). CDD and HDD are obtained from the National Oceanic and Atmospheric Administration. The subsample considers 48 contiguous states (excluding Alaska, Hawaii, and Washington DC) due to limited availability of weather (EDD) data.

Panel A: Across all 51 states (including Washington DC) in U.S.

	Equally-weighted	Population-weighted
Corr. with R_m (%)	0.226	0.260
Std. dev. (%)	0.047	0.043
RRA	18.4	18.1
RRA (s.e.)	7.4	8.4
Implied rf (%)	13.9	19.9
Pricing error	0.0	0.0

Panel B: High- and Low-EDD-volatility states

	Low EDD Volatility		High EDD Volatility	
	Aggregate	State	Aggregate	State
Corr. with R_m (%)	0.335	0.258	0.338	0.263
Std. dev. (%)	0.036	0.045	0.031	0.041
RRA	20.2	17.4	20.0	18.9
RRA (s.e.)	11.7	7.4	12.9	10.2
Implied rf (%)	37.5	17.3	42.3	23.7
Pricing error	0.0	0.0	0.0	0.0

TABLE IX. PREDICTABILITY TESTS

Panel A shows the correlations between various consumption risk variables and an annual NBER business cycle variable defined as the fraction of a year spent in non-recession. In Panel B, results from predictability regression

$$R^e_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1},$$

are presented. R^e_{t+1} is the next year's stock excess return, X_t is the predictive variable, and ε_t is random noise. Predictive variables are components (residential, commercial, industrial, and total) of December to December electricity growth, book-to-market ratio (b/m), investment to capital ratio (i/k), net equity expansion (ntis), percent equity issuing (eqis), consumption wealth ratio (cay), dividend yield (dy), earnings price ratio (ep), annual garbage growth rate of Savov (2010) (gg), and year-on-year fourth quarter expenditure growth by Jagannathan and Wang (2007) (cg_q4). b/m, i/k, ntis, eqis, cay, dy, and ep are obtained from Goyal and Welch (2008) website. In Panel C, predictive regression results using Fama-French 12 industry excess returns are shown. Predictive variables are electricity growth (Dec-Dec, industrial), percent equity issuing (eqis), and consumption wealth ratio (cay). Parameter estimates for β and R^2 (first row) and associated boostrap *p*-values (second row in parenthesis) are reported . For each regression, intercept is included but not shown. Standard errors are shown in parentheses. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively. The bootstrap procedure detailed in Goyal and Welch (2008) accounts for the persistence in the predictor, cross-correlation in error terms and small-sample problem. We consider the 1961–2002 time period due to a change in the electricity usage sector definition in 2003.

Panel A. Correlation with NBER recession variable

Consumption Risk	Correlation with NBER variable
Electricity: Residential (Dec-Dec)	0.2942
Electricity: Commercial (Dec-Dec)	0.2086
Electricity: Industrial (Dec-Dec)	0.5746
Electricity: Total (Dec-Dec)	0.4868
Garbage	0.4253
Q4-Q4 (Seasonally Adjusted)	0.5506
Q4-Q4 (Seasonally Unadjusted)	-0.1037
PJ	-0.1812
cay	-0.0351

TABLE IX (CONTINUED)

Panel B. Predictability of Excess Market Returns

Prediction Variables	Coefficient [p-value]	Predictive Regression R^2 [p-value]
Electricity: Residential (Dec-Dec)	-0.2509	0.0071
	[0.298]	[0.601]
Electricity: Commercial (Dec-Dec)	-0.7103	0.0195
	[0.194]	[0.372]
Electricity: Industrial (Dec-Dec)	-0.9102**	0.0968**
	[0.026]	[0.047]
Electricity: Total (Dec-Dec)	-0.9859*	0.0604
	[0.059]	[0.120]
b/m	0.0649	0.0103
	[0.609]	[0.625]
ik	-9.2636	0.0315
	[0.152]	[0.260]
ntis	-1.8608	0.0311
	[0.154]	[0.271]
eqis	-0.6736**	0.1066**
	[0.030]	[0.034]
cay	4.6631**	0.2282***
	[0.016]	[0.002]
dy	0.0620	0.0212
	[0.187]	[0.364]
ep	0.0784	0.0365
	[0.266]	[0.250]
gg	-0.8845	0.0232
	[0.160]	[0.342]
cg_q4	-3.4692*	0.0717*
	[0.055]	[0.083]

TABLE IX (CONTINUED)

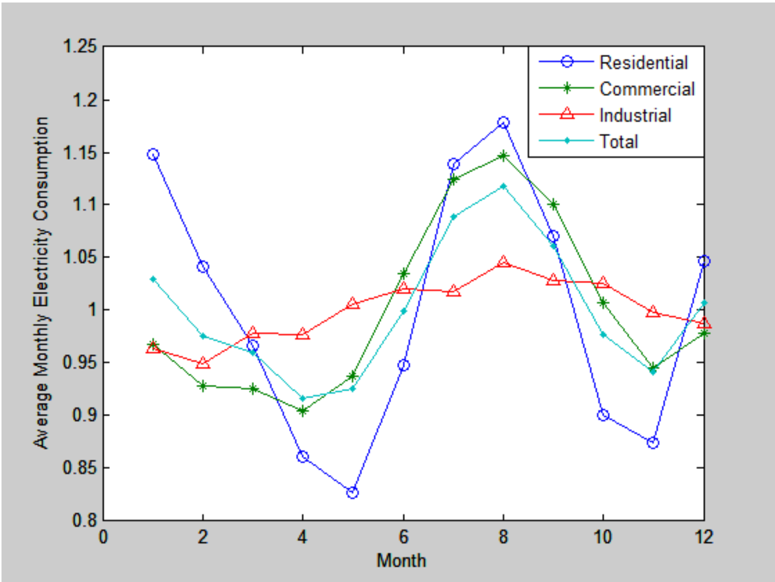
Panel C. Predictability of Fama-French 12 Industry Excess returns

Fama-French 12 Industry		NoDur	Durbl	Manuf	Enrgy	Chems	Buseq
Electricity	coefficient	-1.3714***	-1.6722***	-1.1358***	-0.0771	-1.1379***	-0.9395
	p-value	[0.003]	[0.005]	[0.009]	[0.466]	[0.003]	[0.108]
	R^2	0.1915***	0.1749***	0.1430**	0.0006	0.1786***	0.0396
	p-value	[0.005]	[0.006]	[0.015]	[0.881]	[0.006]	[0.208]
eqis	coefficient	-0.6414*	-0.3246	-0.8371**	-0.5170*	-0.5906**	-0.9465**
	p-value	[0.051]	[0.252]	[0.011]	[0.089]	[0.035]	[0.049]
	R^2	0.0842*	0.0132	0.1561***	0.0514	0.0967**	0.0808*
	p-value	[0.063]	[0.458]	[0.009]	[0.145]	[0.047]	[0.072]
cay	coefficient	5.0218***	5.1331**	4.0698**	2.3800	4.6619***	4.4696
	p-value	[0.006]	[0.033]	[0.031]	[0.159]	[0.005]	[0.110]
	R^2	0.2305***	0.1480**	0.1648***	0.0487	0.2691***	0.0805*
	p-value	[0.001]	[0.013]	[0.010]	[0.169]	[0.001]	[0.081]

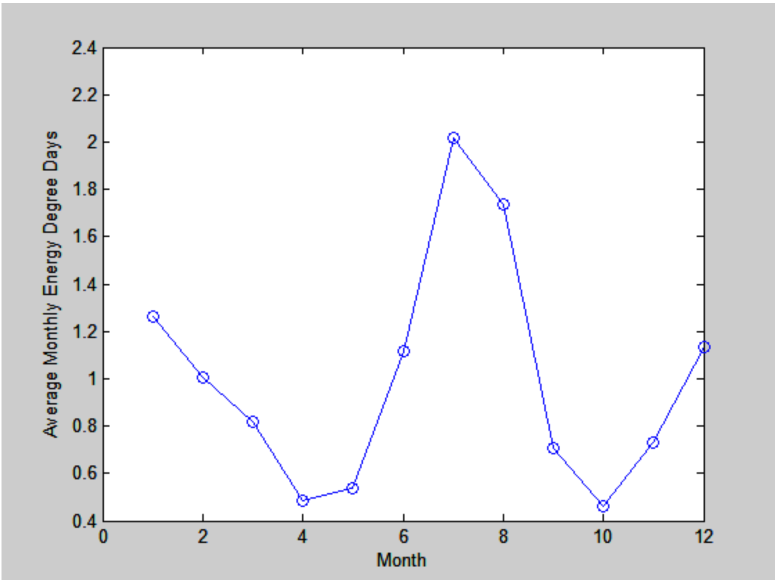
Fama-French 12 Industry		Telcm	Utils	Shops	Hlth	Money	Other
Electricity	coefficient	-0.2812	-0.6783*	-1.7956***	-0.7983*	-1.4609***	-0.9185*
	p-value	[0.310]	[0.068]	[0.002]	[0.078]	[0.004]	[0.051]
	R^2	0.0069	0.0559	0.2054***	0.0528	0.1715***	0.0712*
	p-value	[0.603]	[0.134]	[0.003]	[0.150]	[0.007]	[0.092]
eqis	coefficient	-0.1226	-0.3020	-0.7027*	-0.8476**	-0.7835**	-0.7883**
	p-value	[0.371]	[0.184]	[0.084]	[0.024]	[0.038]	[0.029]
	R^2	0.0026	0.0223	0.0632	0.1197**	0.0991**	0.1054**
	p-value	[0.747]	[0.346]	[0.109]	[0.025]	[0.042]	[0.034]
cay	coefficient	4.6169**	3.2312**	4.8514**	3.6496*	5.0663**	4.4032**
	p-value	[0.023]	[0.039]	[0.043]	[0.061]	[0.019]	[0.043]
	R^2	0.1670***	0.1139**	0.1346**	0.0991**	0.1851***	0.1470**
	p-value	[0.008]	[0.032]	[0.022]	[0.047]	[0.005]	[0.017]

FIGURE 1. SEASONALITY OF ELECTRICITY CONSUMPTION

Panel (a) shows monthly average electricity consumption for 1960-2008. Electricity consumption is based on electricity consumption obtained from the Energy Information Administration (EIA). For each sector, we normalize monthly electricity consumption by each year's mean. Panel (b) shows monthly weather variation for 1960-2008. We measure the average monthly energy degree days (EDD) by the deviation of EDD from its historical mean each month, and then divide it by each month's historical standard deviation. Energy Degree Days (EDD) is the sum of Cooling Degree Days (CDD) and Heating Degree Days (HDD). Historical CDD and HDD are obtained from the National Oceanographic and Atmospheric Administration (NOAA).



(a) Electricity consumption



(b) Historical Energy Degree Days (EDD)

FIGURE 2. COMPARISON OF ALTERNATIVE MEASURES OF CONSUMPTION

Electricity growth is December to December total electricity consumption growth and is based on total electricity consumption data obtained from the Energy Information Administration. Garbage is annual growth rate of municipal solid waste (MSW) provided by Environmental Protection Agency (EPA). Expenditure is annual growth rate of National Income Product Account's seasonally-adjusted annual services and nondurable goods. P-J is the ultimate consumption growth by Parker and Julliard (2005). Q4-Q4 is the year-on-year fourth quarter expenditure growth by Jagannathan and Wang (2007).

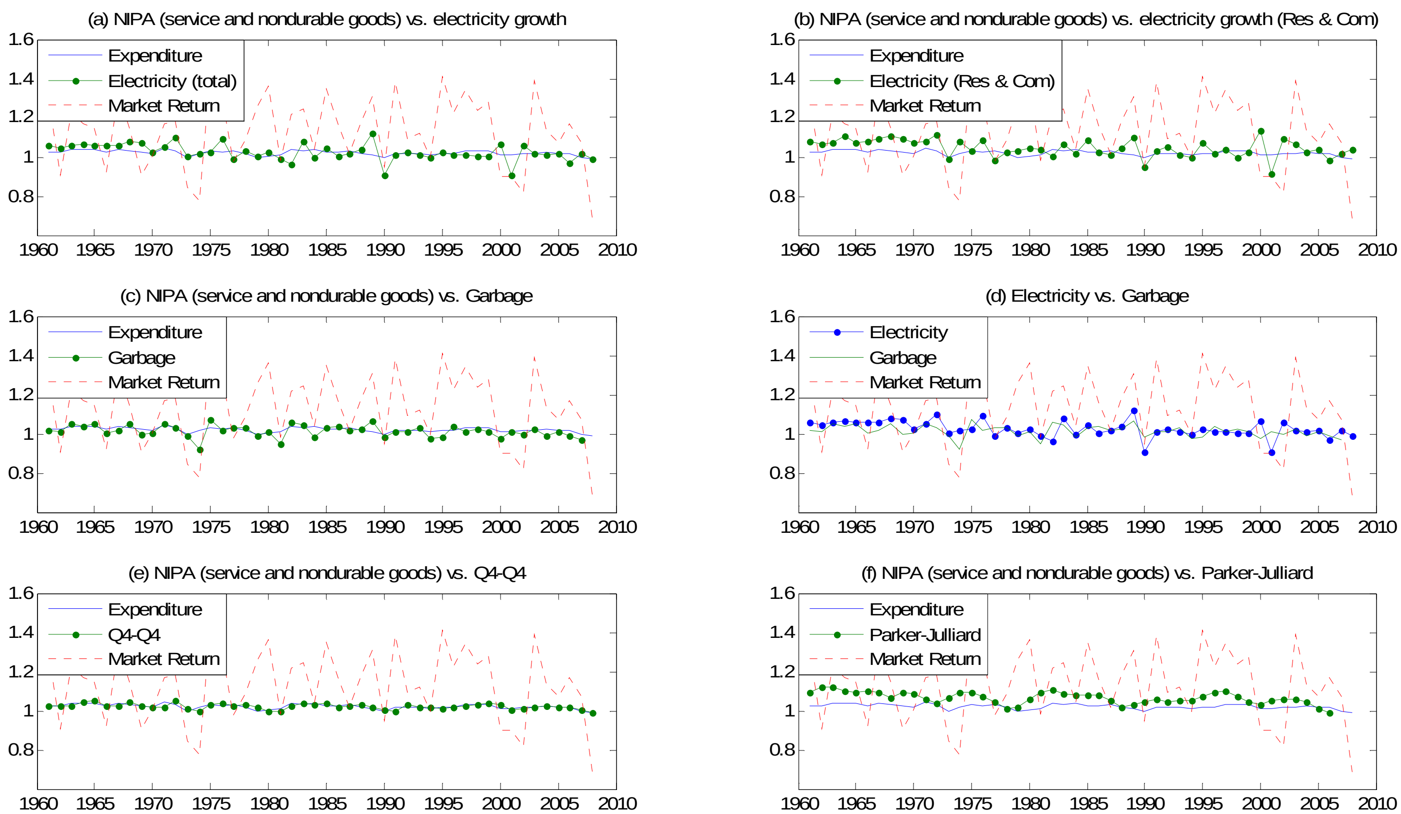


FIGURE 3. DISTRIBUTION OF HISTORICAL WEATHER (EDD) VOLATILITY AND ELECTRICITY CONSUMPTION GROWTH VOLATILITY (U.S. ONLY)

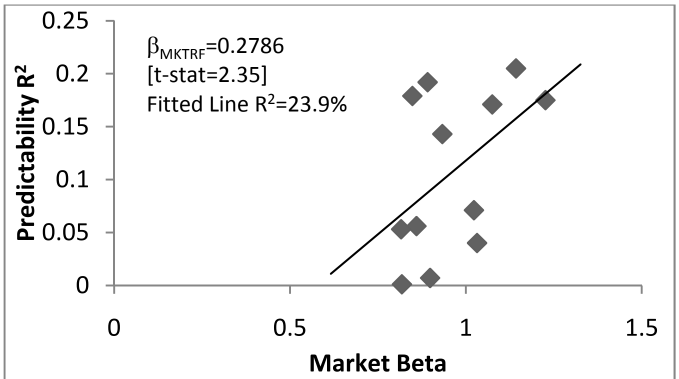
Panel (a) shows historical weather volatility in each state. Historical weather volatility is measured by the standard deviation of energy degree days (EDD) time-series. Energy Degree Days (EDD) is the sum of Cooling Degree Days (CDD) and Heating Degree Days (HDD). Historical CDD and HDD are obtained from the National Oceanographic and Atmospheric Administration (NOAA). Darker colors represent higher historical EDD volatility. Panel (b) shows distribution of electricity consumption growth volatility in each state from 1960 to 2008. Electricity growth is annual total electricity consumption growth and is based on total electricity consumption data obtained from the EIA State Energy Data System. State-level electricity consumption data is divided by state population to obtain per capita electricity consumption in each state. Annual state population is obtained from Surveillance Epidemiology and End Results (SEER) from 1969 to 2007, and from U.S. Census Bureau population estimates from 2008 to 2009. Darker colors represent higher electricity consumption growth volatility.

(a) Historical weather (EDD) volatility

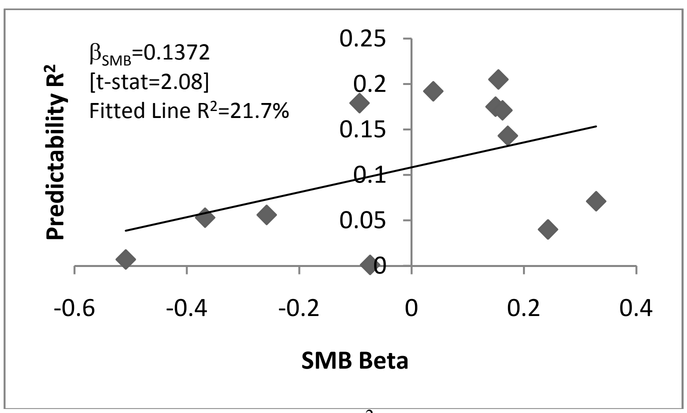
(b) Electricity consumption growth volatility

FIGURE 4. PREDICTABILITY OF FAMA-FRENCH 12 INDUSTRY EXCESS RETURNS

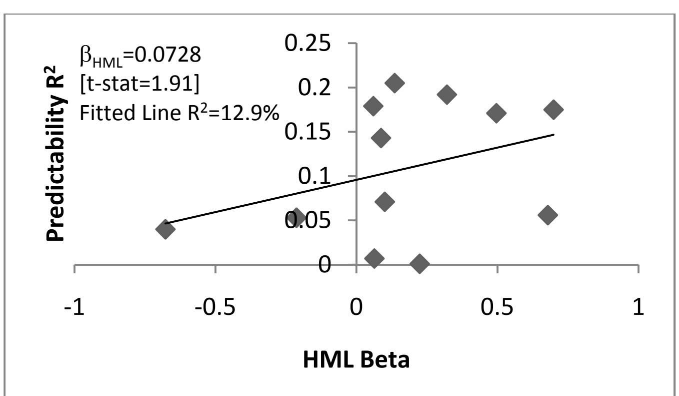
We first run predictive regressions using the following model: $R^e_{FF12,t+1} = \alpha + \beta X_t + \varepsilon_{t+1}$, where $R^e_{FF12,t+1}$ is the next-year excess return on each of the Fama-French 12 industries, X_t is the December-December industrial electricity consumption growth, and ε_t is random noise. We then estimate the three factor loadings for each industry using the usual time-series regressions: $R^e_{FF12,t} = \alpha + \beta_{MKTRF} MKTRF_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \varepsilon_t$, where $R^e_{FF12,t}$ denotes the excess return on each of the 12 Industries, $MKTRF_t$ is excess market return, SMB_t is the SMB factor, HML_t is the HML factor, and ε_t is random noise. The figures then plot the R^2 from the predictive regressions vs. each of the three factor loading across the 12 industries. We consider the 1961–2003 time period due to a change in the electricity usage sector definition in 2003.



(a) Predictability R^2 vs. Market beta



(b) Predictability R^2 vs. SMB beta



(c) Predictability R^2 vs. HML beta