Household Production and Asset Prices

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Abstract

We empirically examine the asset pricing implications of the Beckerian framework of household production, where utility is derived from both market consumption and home produced goods. We propose residential electricity usage as a real-time proxy for the service flow from household capital, as electricity is used in most modern-day household production activities and it cannot be easily stored. Using U.S. residential electricity usage from 1955 to 2012, our model based on household production explains the equity premium and the cross section of expected stock returns (including those of industry portfolios) with an R^2 of 71%.

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1 Introduction

The consumption decision of an investor is the cornerstone to asset pricing. A key insight from the standard consumption-based capital asset pricing model (CCAPM, see Rubinstein (1976), Lucas (1978), and Breeden (1979)) is that the expected excess return of an asset is determined by the co-movement of the asset return with aggregate consumption growth. Despite its intuitive appeal, this prediction found little support among the early empirical tests in both the time-series dimension (see Hansen and Singleton (1982) and Mehra and Prescott (1985)) and the cross-sectional dimension (see Breeden, Gibbons, and Litzenberger (1989)). To resolve these challenges while preserving the intuitive framework of the CCAPM, extant literature has explored modifications in investor preferences, incomplete markets, market imperfections, and alternative ways of measuring aggregate consumption risk.[1]

In this paper, we explore a simple extension of the standard CCAPM by incorporating important insights from the household production literature, in which a household consumes goods produced at home, such as meals and clean clothes (Becker (1965), Lancaster (1966), and Muth (1966), among others).[2] While household production has been shown to be important, measuring it presents a major empirical challenge.[3] We help to meet the empirical challenge by proposing an intuitive real-time proxy for household production: the residential usage of electricity.

In modern life, many household production activities use electricity. For example, in the process of producing and consuming a meal, food may have been stored in a freezer, defrosted in a microwave oven, and cooked in an electric oven. Consequently, the residential usage of electricity captures the service flow from household capital. Importantly, due to technological limitations, electricity cannot

[1]Related papers include Constantinides (1990), Epstein and Zin (1991), Constantinides and Duffie (1996), Campbell and Cochrane (1999), Bansal and Yaron (2004), Hansen, Heaton, and Li (2008), Malloy, Moskowitz, and Vissing-Jorgensen (2009), Ait-Sahalia, Parker, and Yogo (2004), Parker and Julliard (2005), Yogo (2006), Jagannathan and Wang (2007), and Santos and Veronesi (2010), among others.

[2]According to Becker (1965), "Economic development has led to a large secular decline in the work week, so that whatever may have been true of the past, today it is below fifty hours in most countries, less than a third of the total time available. Consequently the allocation and efficiency of non-working time may now be more important to economic welfare than that of working time; yet the attention paid by economists to the latter dwarfs any paid to the former."

[3]See Benhabib, Rogerson, and Wright (1991) and Greenwood and Hercowitz (1991), among many others, for the benefit of incorporating household production into economic models. See Juster and Stafford (1991) and the references therein for the measurement problem.

be easily stored: Once produced, it is either consumed or "wasted" (i.e., dissipated into thermal energy). As a result, residential electricity usage is likely to track household production in real time. Finally, since electric utilities are subject to extensive disclosure requirements, electricity usage is accurately measured at high frequencies and the data are available. In the United States, monthly residential electricity usage data are available from 1955 to the present, allowing us to measure the household production activity more accurately. Indeed, a detailed breakdown of electricity usage at home available for the period 1999 to 2012 confirms that household production activities are the main drivers of the variation in the total residential electricity usage.

Employing residential electricity usage data, our paper becomes one of the first to directly test the asset pricing implications of the Beckerian framework of household production. In our model, household consumption is produced at home with household capital, and a representative household then derives utility from both home produced goods and market consumption.[4] This modeling approach is relatively standard in the household production literature, and is similar to those used by Greenwood, Rogerson, and Wright (1993) and Greenwood, Seshadri, and Yorukoglu (2005), among others. In addition, we model the household's intertemporal utility using Epstein and Zin's (1989) recursive preferences, which differentiate the elasticity of intertemporal substitution (EIS) from risk aversion. Each period, the agent uses her wealth to purchase market consumption, new household capital, and invests in financial assets. The agent also chooses the intensity of utilizing household capital in producing home goods. The agent maximizes the recursive utility subject to intertemporal budget constraints. The resulting pricing kernel is a log-linear three-factor model that includes market consumption growth, household consumption growth, and the return on the market consumption wealth portfolio. Our proxy for market consumption goods is the standard NIPA consumption on nondurables and services. The proxy for household production is residential electricity usage. Following common practice (e.g., Epstein and Zin (1991) and Yogo (2006)), we proxy the market consumption wealth portfolio by the stock market return.

Household production risk arises in the model because the agent derives utility from a bundle of both market consumption goods and household produced goods. Similar to a decrease in market

[4]Alternatively, we can think of the utility being derived from a final consumption good produced from market-purchased consumption goods using the household production technology.

consumption, a drop in home produced goods will increase the marginal utility. A drop in household consumption can result as existing household capital stock depreciates and consumers spend less in new appliances, or cooking and laundering activities decline as households cut expenditures on food and new clothes, and so on. All these mechanisms translate to a decrease in residential electricity usage. A financial asset's exposure to household production risk, measured by its electricity beta or the covariation between the asset return and electricity growth, becomes a determinant of the expected return. Specifically, compared to a stock with a high electricity beta, a stock with a low electricity beta pays more when household consumption is low. The payoff from the stock could be used to increase household production through purchasing new appliances or more food and/or clothes. Hence, a stock with a low electricity beta is preferred and demands a lower expected return.

We test the time-series and cross-sectional moment conditions simultaneously using the Generalized Method of Moments (GMM). We match annual stock portfolio returns with year-on-year growth rates in residential electricity usage, which measure the changes from a given month of the year to the same month of the following year. This alleviates seasonalities in residential electricity usage, in particular those induced by weather changes.

In our baseline asset pricing tests, we use the year-on-year growth rate of fourth-quarter standard NIPA consumption following Jagannathan and Wang (2007), and the year-on-year growth rate of December residential electricity usage. The sample period is 1955–2012 (and thus 1956–2012 for the growth rates). NIPA consumption growth and residential electricity growth are positively correlated (correlation = 0.354 with a standard error of 0.083), although electricity growth is more than three times as volatile. While the correlation is low between electricity growth and market returns, the variations in electricity growth are more responsive to recessions than consumption growth, especially in more recent years. We confirm that the pro-cyclical components of residential electricity usage mostly come from household appliances used in home production.

Electricity growth is positively correlated with the growth rate of the net stock of household appliances (correlation = 0.297 with a standard error of 0.104), supporting the idea that electricity usage captures the service flow from household capital. Furthermore, electricity growth is three times more volatile than the growth rate in household appliances, suggesting that household production can vary considerably due to changing utilization of the existing household capital. Finally, we also obtain the data on average hours of household activities from the 2003–2012 Time Use Surveys of the Bureau of Labor Statistics, and find that electricity growth and housework hours growth is positively correlated (correlation = 0.304 with a standard error of 0.207), supporting the idea that electricity usage also reflects time spent in household activities.

We then test different asset pricing models by fitting both times-series and cross-sectional moments. The test portfolios include both the 25 Fama-French (1996) size and book-to-market portfolios and the 17 industry portfolios. Our electricity-based model (labeled CE-EZ) performs well. It fits the equity premium and the cross section of average stock returns at a relatively low risk aversion of about 36 and a high R^2 of 71%. While a risk aversion of 36 may still appear high, it is worth noting that we are fitting the times-series and cross-sectional asset pricing moments *simultaneously* while the existing literature usually focuses on one set of moments alone. The notable exception is Yogo (2006) where a risk aversion of more than 170 is required.

The performance of our electricity-based model compares favorably with the results generated by several existing models on the same set of 25 Fama-French portfolios and 17 industry portfolios: The standard power utility consumption model (which is essentially CCAPM) requires a risk aversion of more than 100 and yields an R^2 of less than 20%; augmenting the standard consumption model with a market return factor achieves a risk aversion of 78 and an R^2 of 24%; Finally, the Fama-French (1993) three-factor model generates an R^2 of 35%. To compare the R^2 values across models, we use the bootstrap method. In 86% of the 10,000 bootstrapped samples, the R^2 of CE-EZ is higher than that of the Fama-French three-factor model — equivalently, the null hypothesis of equal R^2 is rejected with a p-value of 14%.

The success of our CE-EZ model arises from the capability of residential electricity growth in capturing the cross-sectional variation in the exposure to household production risk. For example, the correlation between the average excess returns on 25 Fama-French portfolios and their electricity betas is 0.88. Compared to growth and large stocks, value and small stocks are associated with higher risk with respect to household consumption. These stocks offer lower payoffs when the marginal utility is high due to declines in home produced goods, and investors demand higher expected returns in order to hold these stocks.

The electricity beta also explains the cross-sectional variation in the average returns of industry portfolios, arguably one of the biggest empirical challenges for many existing asset pricing models. The correlation between the average excess returns on 17 industry portfolios and their electricity betas is 0.48. For example, consumer product, food, and clothing industry portfolios have high electricity betas, consistent with their high average returns. These are precisely the industries whose products require additional household production activities to yield final consumption goods (e.g., meals and clean clothes). As a result, these industries are more subject to household production risk. In contrast, industrial sectors, such as steel and fabricated (metal) products, are less subject to household production risk and therefore earn lower average returns.

We have emphasized the importance of measuring the service flow from household capital. When we replace residential electricity growth with the growth rate of the net stock of household capital, the model's performance deteriorates substantially: the risk aversion increases from 36 to 75 and R^2 drops from 71% to 47%. This result highlights that the success of a household production model hinges on using correct empirical measures.

Additional analysis confirms the robustness of our results. First, orthogonalizing residential electricity growth on a weather change variable does not significantly alter the asset pricing performance, suggesting that any potential weather effect remnant in our year-on-year electricity growth is not driving the results. Second, we find that residential electricity usage does contain important economic information. We simulate a noise factor that, by construction, does not contain additional information, but otherwise matches the mean and standard deviation of our residential electricity growth as well as its correlations with the other two factors in our model. We find the noise factor to perform significantly worse than the true residential electricity growth factor.

While the electricity beta does a better job than the standard NIPA consumption beta in explaining the cross-sectional variation in average returns, removing consumption growth from our model significantly reduces the cross-sectional R^2 from 71% to 50%. Hence, both consumption and electricity growth rates are useful, consistent with the predictions of a household production model.

Our pricing results become weaker when we include all quarter cycles (Q1-to-Q1 consumption growth and March-to-March electricity growth, and so on, in addition to the Q4-to-Q4 consumption growth and December-to-December electricity growth examined in the baseline case). This result is consistent with the findings of Jagannathan and Wang (2007) and Jagannathan, Marakani, Takehara, and Wang (2012), who attribute it to a calendar cycle effect. In the U.S., the fourth quarter and specifically the month of December coincide with the end of the tax year and the Christmas holiday. This is probably when investors have more time for household production activities and feel the need to review their consumption and portfolio choice decisions; consequently, asset pricing models should perform better over the Q4-to-Q4 cycle.[5] It is worth noting that even with all quarter cycles included, our electricity-based model still outperforms other consumption-based models by a big margin.

Overall, our results suggest that a simple extension of the standard CCAPM based on insights from the household production literature goes a long way towards resurrecting consumption-based asset pricing models. Our paper contributes to a growing literature that proposes alternative measures of consumption risk to improve the performance of consumption-based models. Savov (2011) argues that garbage is a better measure of consumption. Ferson and Constantinides (1991) and Yogo (2006) consider durable consumption goods in asset pricing tests. Malloy, Moskowitz, and Vissing-Jorgensen (2009) show that consumption of high-income individuals can help explain asset prices. Ait-Sahalia, Parker, and Yogo (2004) show that consumption of luxury goods help explain the equity premium. Parker and Julliard (2005) argue that "ultimate" consumption risk — covariance between returns and consumption growth cumulated over many quarters — explains the cross section of stock returns. Kroencke (2013) shows that unfiltered NIPA consumption performs as well as garbage in asset pricing tests, and suggests that fourth-quarter NIPA consumption in Jagannathan and Wang (2007) is related to unfiltered NIPA consumption. Complementary to these studies, we show that, using residential electricity usage as a direct proxy for the service flow from household production capital, the Beckerian framework of household production helps to explain the cross-sectional variation in expected returns with a much smaller risk aversion parameter.

[5] Further evidence of end-of-year portfolio adjustment is provided in Møller and Rangvid (2014), which also include a thorough review of the relevant literature.

The asset pricing tests in our paper point to a 40% share for electricity, which we use to measure home produced consumption goods. The electricity data are the quantities used (namely, in kilowatthours), and we provide empirical evidence on the link between electricity usage and household capital and housework hours. Hence, our results suggest a 40% share of household consumption in the utility function[6] and a ratio of 40% : 60% between the values of household and market consumption goods — that is, home produced goods, although not purchased using income from the market, are valued by consumers at a level of about 2/3 of the consumption goods purchased from the market. This result is consistent with the household production literature that emphasizes a significant role of the home sector in consumer decisions and the macroeconomy. Benhabib, Rogerson and Wright (1991) cite time use surveys which show an average married couple spending about 33% of the time in market work and about 28% in household work, and studies that estimate the home produced output at a level as high as half of the GDP. In Greenwood, Seshadri and Yorukoglu (2005) the shares of market consumption and household consumption are 0.33 and 0.2, respectively, suggesting a split of 62.5% : 37.5% between the two goods.[7]

Household production also has important implications in the macroeconomics literature regarding economic growth (Devereux and Locay (1992)), comovements among components of aggregate expenditures (Fisher (1997)), impact of tax and other fiscal policies (McGrattan, Rogerson, and Wright (1995)), and consumption volatility (Baxter and Jermann (1999)), among others. While we examine a simple partial equilibrium household production model in order to isolate in a parsimonious way its incremental asset pricing contribution, we hope that our novel measure — residential electricity — will be of value to a broad range of macroeconomic studies.

The rest of the paper proceeds as follows. Section 2 models household production and the utility function, and derives the pricing kernel and the pricing equation. Section 3 describes the data and provides summary statistics for the main variables. Section 4 presents our empirical results. Section

[6]We are not using the dollar expenditures by households on electricity, and households certainly do not spend 40% of their income to purchase electricity.

[7]Most of the papers in the household production literature model the agent utility using a CES aggregator over market consumption, household consumption, and leisure. Our setup is different in two regards. First, since we are considering general Epstein-Zin preferences, we choose a simpler intra-period utility function — the Cobb-Douglas form which is a special case of the general CES aggregator. Second, we abstract away from leisure choice. An earlier version of our paper did try to incorporate leisure but the empirical data on time use is so poor that it does not contribute much to the asset pricing performance.

5 concludes. The appendices collect additional details of the model.

2 Household production and asset pricing

2.1 The household production model

Consistent with the literature on household production (see Greenwood, Rogerson, and Wright (1993), Greenwood, Seshadri, and Yorukoglu (2005), among others), we consider a representative household whose intra-period utility is derived from both market consumption (C_t) and consumption of household produced goods (E_t):

$$V_t = C_t^{1-\alpha} E_t^{\alpha}, \tag{1}$$

where $0 < \alpha < 1$. We subsequently propose to use electricity to measure household production and present empirical evidence on the link between electricity usage and household factors of production, which includes the household capital stock and the time spent in housework. Alternatively, in the spirit of Becker (1965), we could interpret the above equation as a production function where the household uses household capital and labor to turn market consumption goods into final consumption goods, from which utility is derived. For example, a meal cooked at home combines food produced in the market with home cooking that uses household capital and time to create the final good.

The intra-period utility is imbedded in Epstein-Zin (1989) recursive preferences:

$$U_t = \left((1-\delta) V_t^{1-\frac{1}{\psi}} + \delta \left(\mathbf{E}_t [U_{t+1}^{1-\gamma}] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right)^{\frac{1}{1-\frac{1}{\psi}}}. \tag{2}$$

Here, $0 < \delta < 1$ is the time discount factor, γ is the risk aversion parameter, and ψ is the elasticity of intertemporal substitution.

Our simple model abstracts away from the consumption/leisure choice as analyzed by Eichenbaum, Hansen, and Singleton (1988). It also does not consider the firm production decision in a general equilibrium setting, as analyzed by Greenwood, Rogerson, and Wright (1993). These simplifications allow us to isolate the incremental asset pricing contribution of household production relative to a standard CCAPM that only focuses on the market consumption choice of a representative agent.

2.2 Pricing kernel

The agent maximizes the recursive utility subject to intertemporal budget constraints. As detailed in Appendix A, household consumption is produced at home using household capital, which depreciates over time. Each period, the agent uses her wealth to purchase market consumption, new household capital, and invests in financial assets. The agent also chooses the intensity of utilizing household capital to produce household consumption goods. In equilibrium, the wealth portfolio, whose return appears in the pricing kernel, is expanded to include the value of the household capital stock. Further, we show that the return on this expanded wealth portfolio is equal to the return on the usual portfolio of aggregate market consumption claim. Ultimately, this leads to the pricing kernel

$$M_{t+1} = \delta^{\theta}\Big(\frac{C_{t+1}}{C_t}\Big)^{-\frac{\theta}{\psi}-\alpha\theta(1-\frac{1}{\psi})}\Big(\frac{E_{t+1}}{E_t}\Big)^{\alpha\theta(1-\frac{1}{\psi})}R_{g,t+1}^{\theta-1}. \tag{3}$$

Here, $\theta=(1-\gamma)/(1-\frac{1}{\psi})$ and $R_{g,t+1}$ is the return on the market consumption wealth portfolio.[8]

The pricing kernel exhibits a log-linear factor structure. Specifically, the log pricing kernel is

$$\log M_t = \theta\log\delta - b_1\Delta c_t - b_2\Delta e_t - b_3 r_{g,t}. \tag{4}$$

Among the three factors, Δc and Δe are log growth rates, and r_g is the log return on the wealth portfolio. The constants b_i are factor prices of risk and are related to the preference parameters.

$$b_1 = \theta\Big(\frac{1}{\psi}+\alpha\big(1-\frac{1}{\psi}\big)\Big), \tag{5}$$

$$b_2 = -\theta\alpha(1-\frac{1}{\psi}), \tag{6}$$

$$b_3 = 1-\theta. \tag{7}$$

[8] As anticipated, the result is the same as in Bansal, Tallarini, and Yaron (2004).

For convenience of subsequent exposition, we use the vector notation

$$f_t = [\Delta c_t \quad \Delta e_t \quad r_{g,t}]', \tag{8}$$

$$\mu_f = \mathbf{E}[f_t], \tag{9}$$

$$b = [b_1 \quad b_2 \quad b_3]', \tag{10}$$

to rewrite the pricing kernel as

$$\log M_t = \mu_m - (f_t - \mu_f)' b, \tag{11}$$

where μ_m is a constant.

2.3 Estimation

We use GMM as a unified approach to estimate both the log-linear factor specification and the original pricing kernel of the model. Let $R_t = (R_{1,t}, R_{2,t}, \ldots, R_{N,t})'$ denote the vector of stock returns for N test assets, $R_{f,t}$ be the risk-free rate, and $R_t^x = R_t - R_{f,t-1}$ be the excess returns. Accordingly, for log returns, let $r_t = \log R_t$, $r_{f,t} = \log R_{f,t}$, and $r_t^x = r_t - r_{f,t-1}$. As shown in Appendix B, with the log-linear pricing kernel and under the joint log normality assumption, the pricing equation is

$$\mathbf{E}[r_t^x] + \frac{1}{2}\mathrm{var}\left[r_t^x\right] = \mathbf{E}[r_t^x (f_t - \mu_f)'] b. \tag{12}$$

The corresponding moment conditions are

$$\mathbf{E}\begin{bmatrix} r_t^x + \frac{1}{2}(r_t^x - \mu_{rx})^2 - r_t^x (f_t - \mu_f)' b \\ f_t - \mu_f \\ r_t^x - \mu_{rx} \end{bmatrix} = 0, \tag{13}$$

where $\mu_{rx} = \mathbf{E}[r_t^x]$, and $r_t^x + \frac{1}{2}(r_t^x - \mu_{rx})^2$ are adjusted excess log returns. We estimate the factor prices of risk b, and then compute the implied preference parameters.

To assess the model performance in fitting the cross section of the N stock returns, we compute goodness-of-fit measures. Denote the realized average adjusted excess log return of asset i by

$$\bar{r}_i^x = \frac{1}{T}\sum_{t=1}^{T} r_{i,t}^x + \frac{1}{2}\frac{1}{T}\sum_{t=1}^{T}\left(r_{i,t}^x - \frac{1}{T}\sum_{t=1}^{T} r_{i,t}^x\right)^2. \tag{14}$$

The pricing error is the difference between the realized and model-predicted average excess returns:

$$\epsilon_i = \bar{r}_i^x - \left(\frac{1}{T}\sum_{t=1}^{T} r_{i,t}^x (f_t - \mu_f)'\right) b \tag{15}$$

We compute MAPE, the mean absolute pricing error, as

$$\text{MAPE } = \frac{1}{N}\sum_{i=1}^{N} |\epsilon_i|. \tag{16}$$

We also compute R^2 as 1 minus the ratio of the cross-sectional variance of the pricing errors to the cross-sectional variance of the realized average excess returns.

$$R^2 = 1 - \frac{\frac{1}{N}\sum_{i=1}^{N}(\epsilon_i - \frac{1}{N}\sum_{i=1}^{N}\epsilon_i)^2}{\frac{1}{N}\sum_{i=1}^{N}(\bar{r}_i^x - \frac{1}{N}\sum_{i=1}^{N}\bar{r}_i^x)^2}. \tag{17}$$

Note that this R^2 is different from that in ordinary least sqaures. In particular, a negative R^2 is possible and indicates that a model's pricing errors are worse than assuming that the average excess returns of all test assets are the same and equal to the cross-sectional average of these average excess returns.

To obtain the confidence interval for the R^2 we use the bootstrap method: we re-sample the empirical data to generate 10,000 bootstrap samples, conduct model estimation and obtain the R^2 for each sample, and report the 5th and 95th percentiles. Similarly, to assess the significance of the difference in the R^2 across two models, we estimate both models for each bootstrapped sample, and compare the R^2. For example, if we find that in $(1-z)\%$ of the bootstrapped samples, the R^2 of one sample is higher than that of the other, then we conclude that the null hypothesis of equal R^2s is rejected with a p-value of $z\%$.

The pricing equation can be recast in terms of the beta and the factor risk premia:

$$
\begin{aligned}
\mathbf{E}[r_t^x] + \frac{1}{2}\text{var}\left[r_t^x\right] &= \mathbf{E}[r_t^x(f_t - \mu_f)'] \ \mathbf{E}[(f_t - \mu_f)(f_t - \mu_f)']^{-1} \\
&\quad \times \mathbf{E}[(f_t - \mu_f)(f_t - \mu_f)'] \ b \\
&= \beta' \times \lambda,
\end{aligned} \tag{18}
$$

Following the GMM estimation, we can compute

$$
\beta = \left(\frac{1}{T} \sum_{t=1}^{T} (f_t - \mu_f)(f_t - \mu_f)' \right)^{-1} \left(\frac{1}{T} \sum_{t=1}^{T} (f_t - \mu_f) r_t^{x\prime} \right). \tag{19}
$$

The pricing equation above, which is based on the log-linear pricing kernel and log returns, is in parallel with that for a linear factor model. Specifically, if the pricing kernel itself is linear in the factors,

$$
M_t = \mu_M - (f_t - \mu_f)'b, \tag{20}
$$

then the pricing equation, using excess returns, is

$$
\mathbf{E}[R_t^x] = \mathbf{E}[R_t^x(f_t - \mu_f)']b. \tag{21}
$$

The corresponding moment conditions are

$$
\mathbf{E} \begin{bmatrix} R_t^x - R_t^x(f_t - \mu_f)'b \\ f_t - \mu_f \end{bmatrix} = 0. \tag{22}
$$

For this setup, the mean absolute pricing error, the R^2, and the beta can be similarly defined using excess returns. As emphasized in Cochrane (2005), the GMM estimation of linear factor models is essentially a generalized least squares (GLS) variant of the long-standing approach of time-series and cross-sectional regressions. Appendix C shows that factor betas are theoretically equivalent to (but can be numerically different from) those obtained as slope coefficients from time-series regressions of excess returns on factors.

In subsequent empirical analysis, we use the moment conditions in Eq. (13) based on the pricing equation with adjusted excess log returns $r_t^x + \frac{1}{2}(r_t^x - \mu_{rx})^2$ to estimate the household production model and other preference-based models, whose pricing kernels are log-linear. For truly linear factor models such as the CAPM and Fama-French three-factor models, we estimate the moment conditions in Eq. (22) based on the pricing equation with excess returns R_t^x . In our data, the correlation between the average adjusted excess log returns and the average excess returns across the test assets (25 Fama-French portfolios and 17 industry portfolio) is 0.9995, which validates the comparison of the goodness-of-fit measures between the two sets of estimation results.

We also follow Hansen and Singleton (1982) and directly estimate the original pricing kernel using the moment conditions

$$\mathbf{E}\begin{bmatrix} M_t R_{f,t-1} - 1 \\ M_t R_t^x \end{bmatrix} = 0. \tag{23}$$

The moment conditions based on these Euler equations allow us to directly estimate the preference parameters, including the time discount factor.

As detailed below, our proxy for market consumption, C_t, is NIPA real expenditures on non-durable goods and services. Our proxy for the service flow from household production capital, E_t, is residential electricity usage. Following existing studies, we use the aggregate stock market return $R_{m,t}$ as the proxy for the wealth portfolio return in the estimation. The test assets include the one-year risk-free rate and the annual returns on 25 Fama-French portfolios and 17 industry portfolios.

We use a two-stage GMM estimation procedure. To begin, we obtain the initial values for the parameters by estimating the model moment conditions using the Ordinary Least Square (OLS) regression. These initial estimates allow us to compute the weighting matrix for the first stage GMM. The parameter estimates from the first stage are then used to compute the weighting matrix for the second stage GMM. The weighting matrix has a block-diagonal structure as suggested in Cochrane (2005), and is heteroscedasticity and autocorrelation consistent, and computed following Newey-West (1987) with two lags.[9]

[9] The results and the standard errors are robust to different lag choices.

3 Data

Quarterly real expenditures on nondurable goods and services are obtained from the NIPA tables of the Bureau of Economic Analysis (BEA) for the period of 1955–2012. Monthly U.S. residential electricity usage data are manually collected from two sources: Electric Power Statistics for 1955–1978 and Electric Power Monthlies for 1979–2012. These documents are published each month by the Energy Information Administration (EIA) and report the monthly sales of electric energy in millions of kilowatthours.[10]

To investigate the link between electricity usage and household factors of production, we also obtain the data on household capital and the time spent in household work. Household capital is measured by the year-end real net stock of household appliances obtained from the NIPA tables of the BEA for the period of 1955–2012. Household work time is measured by the average hours of household activities per day by the civilian population (both men and women) from the Time Use Surveys by the BLS for the period of 2003–2012.[11]

To compute per capita values, we obtain the population data from the U.S. Census Bureau. Annual stock returns and risk-free rates are obtained from Ken French's online data library, and are adjusted by the annual inflation rates from the CRSP for the period of 1955–2012.

For the asset pricing tests, we construct and use year-on-year growth rates when quarterly or monthly data are available. A key reason is that residential electricity usage is exposed to strong within-year seasonal effects, such as weather fluctuations. Prior work notes that electricity usage is partly influenced by weather (see Pérez-González and Yun (2013)). Figure 1 shows the normalized electricity usage and energy degree days (EDD) for each month. EDDs are the sum of cooling degree days (CDD) and heating degree days (HDD), which measure summer and winter weather variation, respectively.[12] For each year, we normalize monthly electricity usage and EDDs by

[10] The residential sector consists of living quarters for private households. Total electricity usage accounts for the amount used by ultimate customers, and hence excludes resold or wasted amounts. It also excludes direct use, which is electricity used in power plants for generating electricity.

[11] We do not use the housework hours in Ramey (2009) since the data are largely estimated by interpolation of surveys that were conducted infrequently.

[12] Summer (winter) weather is measured by monthly cooling (heating) degree days (CDD or HDD), which we obtain from the National Oceanic and Atmospheric Administration (NOAA). The daily CDD (HDD) values capture the deviations in daily mean temperatures above (below) 65F, the benchmark at which energy demand is low. As an example, if the average temperature is 75F, the corresponding CDD value for the day is 10 and that of HDD is 0. If

subtracting the means and dividing by the standard deviations. Then for each month of a year, we compute the time-series averages over the sample period. As shown in the figure, the monthly variation in weather conditions and that of electricity demand are positively correlated.

Year-on-year growth measures the change in electricity usage between the same months in two successive years, and thus identifies differences in demand due to changes in economic conditions rather than seasonal weather effects. One may argue that year-on-year electricity usage growth is still subject to residual weather effects (for instance, if December 2010 is unusually cold). As reported subsequently in robustness analyses, we remove the effects of extreme weather variations from the year-on-year electricity usage growth, and find that the residual electricity usage growth (which is orthogonal to weather changes) performs similarly in asset pricing tests.[13]

While heating and cooling consume electricity at home, neither is a major component of residential electricity usage. According to the Energy Information Administration (EIA), in 2009, heating and cooling accounted for only 18.4% and 17.9% of the total residential electricity usage, respectively. A wide range of other household activities account for the remaining 63.7%.[14]

For our tests, we match calendar-year returns to year-on-year December electricity growth rates and year-on-year fourth-quarter NIPA consumption growth rates. Jagannathan and Wang (2007) show that the year-on-year fourth-quarter growth rate in consumption does a good job in explaining cross-sectional variations in average returns of the Fama-French 25 portfolios. In the U.S., the fourth quarter and in particular December coincide with the end of the tax year and the Christmas holiday. This is when investors both feel the need and have the time to review their consumption and portfolio choice decisions; consequently, asset pricing models should perform better by focusing on year-end decisions. Further evidence of end-of-year portfolio adjustment is provided in Møller and Rangvid (2014), which also include a thorough review of the relevant literature.

In computing the growth rates of NIPA consumption, we subtract the expenditures on electricity

the average temperature is 55F, the corresponding CDD value for the day is 0 and that of HDD is 10. The monthly CDD (HDD) values are the sum of daily CDD (HDD) values in each month.

[13]Weather changes may rationally affect asset pricing, as in Bansal and Ochoa (2012).

[14]See U.S. Residential Electricity Consumption by End User at http://www.eia.gov/tools/faqs. We also confirm that weather fluctuation consistently drives about one-third of year-on-year electricity growth over different annual cycles. In addition, cooling becomes almost irrelevant given our focus on December-to-December residential electricity growth rate.

to avoid double counting, although empirically this adjustment has very little effect on our results, as the expenditures on electricity account for less than 2% of the NIPA consumption bundle.[15]

Table 1 reports summary statistics. Compared to the NIPA consumption growth rates, which have a mean of 1.98% and a standard deviation of 1.42%, the growth rate in residential electricity usage is on average higher (mean = 2.99%) and more volatile (standard deviation = 5.68%).[16] Hence, the NIPA consumption is smooth while electricity usage reflects real-time household production activities that can vary substantially. The correlation between the two growth rates is 0.354 and significantly positive. Consumption growth is positively autocorrelated and positively correlated with stock market returns: the correlation is 0.331 and is significantly positive. The correlation between residential electricity growth and the market return is low. The top panel of Figure 2 plots the time series of the two growth rates, with NBER recessions marked by shaded areas. Residential electricity growth appears to be more responsive to recessions, especially during the early 1990s and 2000s.[17]

The pro-cyclical nature of residential electricity usage comes mostly from household appliances used in home production. Starting 1999, annual data on the components of residential electricity usage became available from Annual Energy Outlook. We examine how each component comoves with a business cycle variable defined as the fraction of a year spent in boom according to the NBER recession dating. Nine components positively comove with the business cycle variable: space heating and cooling, TV sets, dishwashers, dryers, furnace fans and boiler circulation pumps,

[15] We do not use the monthly electricity usage data from the NIPA since they are seasonally adjusted, which may have undesirable consequences for asset pricing tests as pointed out by Ferson and Harvey (1992). At the annual frequency, electricity growth from the NIPA are highly correlated with that from the EIA, with a correlation of 0.823.

[16] We report later in Table 2 that the average growth rate of residential electricity usage is almost identical to that of household appliances, and a regression of electricity growth on appliances growth yields a slope coefficient of essentially 1. Hence, the growth of electricity usage at 3% per year is almost entirely due to the increase in household capital stock. The 3% electricity growth does not imply an imbalance vis-a-vis the 2% growth in NIPA consumption (and also in GDP), because the price of household capital (relative to nondurable goods and services) has been decreasing. In other words, as appliances become more affordable over time, households own better and bigger refrigerators, and install washers and dryers at home rather than use coin laundries. A similar trend in durable goods is reported in Yogo (2006). For example, as the price of automobiles falls, households own more and better cars.

[17] For electricity growth, the evidence for time-varying conditional mean is insignificant. As reported in Table 1, the first-order autocorrelation coefficient is -0.228 with a standard deviation of 0.198. When we regress electricity growth on both lagged electricity growth and lagged consumption growth, the coefficients (standard errors) are -0.273 (0.203) and 0.530 (0.391), respectively. Likewise, the evidence for time-varying conditional variance is also insignificant. We estimate a GARCH(1,1) model on the AR(1) residuals of electricity growth. The estimation converges to an ARCH(1) model, with a coefficient (standard error) of 0.182 (0.192).

cooking, cloth washers, refrigerators, and other uses. Together, the nine components account for 76% of the total residential electricity usage and their average covariance with the business cycle variable is 0.0184, 4.2 times the covariance between NIPA consumption growth and the business cycle variable during the same sample period.

The data on the components of residential electricity usage also allows us to determine the key drivers of residential electricity growth. We categorize the components into three broad groups: (1) living comfort (including space heating, water heating, lighting, and furnace); (2) leisure (including TV sets and computer); (3) housework (including refrigerator, freezer, cooking, dishwasher, washer, dryer, and other electronic appliances).[18] By construction, the annual total residential electricity growth rate in year t, Δe_t, is the weighted average of electricity growth rates of the three groups :

$$\Delta e_t = w_{t-1}^{(1)} \Delta e_t^{(1)} + w_{t-1}^{(2)} \Delta e_t^{(2)} + w_{t-1}^{(3)} \Delta e_t^{(3)}, \tag{24}$$

and the variance in total residential electricity growth can be decomposed accordingly:

$$\text{var}\left[\Delta e_t\right] = \text{cov}\left[\Delta e_t,\ w_{t-1}^{(1)} \Delta e_t^{(1)}\right] + \text{cov}\left[\Delta e_t,\ w_{t-1}^{(2)} \Delta e_t^{(2)}\right] + \text{cov}\left[\Delta e_t,\ w_{t-1}^{(3)} \Delta e_t^{(3)}\right]. \tag{25}$$

Divide both sides by var $\left[\Delta e_t\right]$,

$$\begin{aligned} 1 &= \frac{\text{cov}\left[\Delta e_t,\ w_{t-1}^{(1)} \Delta e_t^{(1)}\right]}{\text{var}\left[\Delta e_t\right]} + \frac{\text{cov}\left[\Delta e_t,\ w_{t-1}^{(2)} \Delta e_t^{(2)}\right]}{\text{var}\left[\Delta e_t\right]} + \frac{\text{cov}\left[\Delta e_t,\ w_{t-1}^{(3)} \Delta e_t^{(3)}\right]}{\text{var}\left[\Delta e_t\right]} \\ &= b^{(1)} + b^{(2)} + b^{(3)}. \end{aligned} \tag{26}$$

$b^{(1)}, b^{(2)}$, and $b^{(3)}$ then measure the percentage contributions to the variation in total electricity growth from living-comfort-related usage, leisure activities, and housework, respectively. Using the annual data from 1999 to 2012, we estimate the three percentage contributions to be 23.6%, 12.2%, and 64.2%. Indeed, housework appears to drive most of the variation in the growth rate of residential electricity.

To further evaluate residential electricity usage as a proxy for household production, in Table 2 we investigate the relation between the growth rates of electricity, household capital, and housework

[18] We exclude space cooling from this analysis since it is less relevant for our December-to-December residential electricity growth

time. Panel A reports the summary statistics for the growth rate of the net stock of household appliances. The middle panel of Figure 2 plots appliances growth together with electricity growth. Household appliances grow at almost the same rate as residential electricity usage (3.02% vs. 2.99%). In addition, the growth rate in household appliances is positively correlated with the growth rate in residential electricity usage: the correlation of 0.297 is strongly positive. In fact, a regression of electricity growth on appliances growth produces a slope coefficient of 0.9, which is not significantly different from 1. These results support the idea that electricity usage captures the service flow from household capital. In the meantime, electricity growth is three times more volatile than the growth rate of household appliances, suggesting that household production can vary considerably due to the changing utilization rate of the existing household capital. The residuals from regressing electricity growth on appliances growth may be interpreted as capturing the changes in the utilization rate. While the correlation between electricity growth and stock market returns is low, the residuals or the changes in the utilization rate correlate with the market returns with a correlation of 12% (standard error = 11%).

For the period of 2003–2012, the data on household activities are available from the BLS Time Use Surveys. During this period, the growth rates of housework hours and annual residential electricity usage have very similar means, and are positively correlated: the correlation is 0.304, with a standard error of 0.207. The bottom panel of Figure 2 plots household work hours growth together with electricity growth in this shorter sample period. These results support the idea that electricity usage also reflects time spent in household activities.

4 Empirical results

We estimate both log-linear factor models and the nonlinear pricing kernel based Euler equations with GMM. Estimation of log-linear models allows us to compare with the CAPM and Fama-French three-factor models and assess the goodness of fit. The slopes, which are the factor prices of risk, can also be used to compute the implied preference parameters, except for the time discount factor. Estimation of the pricing kernel based Euler equations yields the preference parameters directly, including the time discount. As shown below, the results from the two approaches are consistent with and thus corroborate each other. We also produce estimation results using two sets of test assets. The default is the larger collection of 25 Fama-French portfolios plus 17 industry portfolios. We also present the results using 25 Fama-French portfolios only. The returns of the industry portfolios are arguably the biggest challenge to many existing asset pricing models. The inclusion of the industry portfolios in the tests is also consistent with the suggestion of Lewellen, Nagel, and Shanken (2010).

4.1 Factor models

Panel A of Table 3 presents the estimation of the linear and log-linear factor models using the larger, default set of stock portfolios. We report factor prices and the implied preference parameters. To assess the model performance in fitting the cross section of stock returns, we compute two goodness-of-fit measures, the mean absolute pricing error MAPE and R^2. Both are defined earlier in Section 2.3. Overall, among the five factor models, our model, CE-EZ, delivers the smallest pricing error and the highest R^2.

We begin with the single factor CAPM. While the price of the market factor is positive and significant, the model generates large pricing errors and a negative R^2.[19] The other single-factor model, C-Power, with Q4-to-Q4 consumption growth as the factor, delivers a smaller MAPE and an R^2 of about 17%. The C-Power model is the log-linear counterpart to the CCAPM, and the result corroborates the evidence reported by Jagannathan and Wang (2007) when they include the industry portfolios as test assets. Since the C-Power model is based on the power utility, the implied risk aversion is high (more than 100).

Embedding consumption into Epstein-Zin preferences leads to the two-factor C-EZ model. With an additional factor, this model reduces the pricing error and improves the R^2 somewhat. In addition, Epstein-Zin preferences decouple risk aversion and the elasticity of intertemporal substitution.

Further incorporating electricity growth in Esptein-Zin preferences yields our preferred model, CE-EZ, motivated by insights from the household production literature. This three-factor model

[19] See Section 2.3 for a discussion of negative R^2 values.

delivers substantial improvement. The average pricing error is lowered to 1.09%, and the R^2 is increased to more than 70%. Moreover, risk aversion is reduced to below 40. The estimation allocates about 40% to household production, with the remaining 60% to market consumption.

Setting the price of risk for the market return factor to zero in the CE-EZ model obtains the CE-Power model, which embeds a Cobb-Douglas function of consumption and electricity in the power utility. Since we find a highly significant estimate for this price of risk in the CE-EZ model, we expect the asset pricing performance to decline under the CE-power model. Indeed, compared to the CE-EZ model, the CE-Power model obtains a higher risk aversion of about 57 and a lower R^2 of about 49%. In addition, the R^2 of the CE-EZ model is higher than that of the CE-Power model in 72% of 10,000 bootstrapped samples of the original data — equivalently, the null hypothesis of equal R^2s is rejected with a p-value of 28%. Overall, the significant price of risk for the market factor and the better asset pricing performance of the CE-EZ model favor Epstein-Zin preferences over the power utility.

The results of the CE-EZ model corroborate a large literature on the equity premium puzzle that find risk aversion $\gamma > 1$. The estimate of γ and the positive price of risk for the market return factor together imply a small ψ as well as $\gamma < 1/\psi$, or a preference for late resolution of uncertainty. Appendix D provides a more detailed discussion. The CE-Power model, based on the power utility, is equivalent to setting $\gamma = 1/\psi$ and implies indifference with respect to temporal resolution of uncertainty. As discussed above, compared to the CE-EZ model, the asset pricing performance is somewhat reduced, although the tenor of the results largely remains in the CE-Power model.

Finally, we find that our three-factor CE-EZ model, motivated by the economic intuition of household production, does a better job than the empirical three-factor model of Fama and French (1993). The estimation results when we apply the Fama-French three-factor model to 25 Fama-French portfolios plus 17 industry portfolios indicate a larger MAPE of about 1.6% and a lower R^2 of 35%. In addition, in 86% of the bootstrapped samples, the R^2 of CE-EZ is higher than that of the Fama-French three-factor model — equivalently, the null hypothesis of equal R^2s is rejected with a p-value of 14%.

Figure 3 graphically illustrates the goodness of fit of the five models. For each model, we plot the average realized returns on the 42 portfolios in small circles against the model-predicted expected returns. If a model does a good job of explaining the cross-sectional variation in average returns, we would expect the small circles to line up along the 45 degree line. This is the case for our CE-EZ model, consistent with the result that the CE-EZ model has the highest R^2 in the asset pricing test.

Panel B of Table 3 reports the estimation results using only 25 Fama-French portfolios. Except for the CAPM, all the other models perform better in pricing this smaller set of test assets, with lower pricing errors and higher R^2. For example, the R^2 increases to 55% for the single factor C-Power, consistent with the results in Jagannathan and Wang (2007). Still, our CE-EZ model yields the best performance. For example, the R^2 is almost 86% for CE-EZ, higher than that of the Fama-French three-factor model ($R^2 = 65\%$), which is designed to explain the cross-sectional return variation in size and book-to-market sorted portfolios. Further, in 74% of the bootstrapped samples, the R^2 of CE-EZ is higher than that generated by the Fama-French three-factor model.

4.2 Euler equations with pricing kernels

For the four models, C-Power, C-EZ, CE-Power, and CE-EZ, we can also estimate the Euler equations directly to obtain the preference parameters. The results are reported in Table 4. Overall, the parameter estimates are close to those implied by the factor prices in the log-linear models. As shown in Panel A, the model with consumption in the power utility (which corresponds to CCAPM) produces a large risk aversion estimate. With Epstein-Zin preferences, the C-EZ model reduces risk aversion. Finally, incorporating residential electricity usage growth further lowers the risk aversion parameter.

4.3 Factor betas

To better understand the success of our CE-EZ model, we report in Table 5 the betas of the portfolio excess returns on the factors — NIPA consumption growth, electricity growth, and the market returns. The factors are based on the GMM estimation using 25 Fama-French portfolios and 17 industry portfolios jointly, while for expositional convenience, the results are presented separately: Panels A to D report the average adjusted excess log returns and the factor betas for 25 Fama-French portfolios, while Panel E presents the betas for 17 industry portfolios, sorted by their average excess returns.

The average adjusted excess log returns of 25 Fama-French portfolios confirm the existence of size and value premiums in our sample period: high book-to-market, or value, portfolios earn higher returns than low book-to-market, or growth, portfolios; small stock portfolios earn higher returns than large stock portfolios (with the exception of the small growth portfolio).

Panel B shows that the consumption beta does a reasonable job of explaining the average return variation across 25 Fama-French portfolios, which is consistent with the findings of Jagannathan and Wang (2007). In particular, value stocks have higher consumption betas than growth stocks, and small stocks have higher consumption betas than large stocks. Overall, across the 25 Fama-French portfolios, the correlation between the average excess returns and the consumption betas is about 0.75.

Panel C reports on the electricity betas, which line up even better with the average excess returns of 25 Fama-French portfolios. Value stocks have higher electricity betas than growth stocks and, just like the returns, with the exception of the small growth portfolio, small stocks have higher electricity betas than large stocks. Overall, the correlation between the average excess returns of 25 Fama-French portfolios and their electricity betas is 0.88. These results suggest that, compared to growth and large stocks, value and small stocks offer lower payoffs when the marginal utility is high due to declines in home produced goods, and investors demand higher expected returns in order to hold these stocks.

For completeness, we report the betas on the market return factor in Panel D. As has been previously documented for the CAPM, the market beta does not explain the cross-sectional return variation at all. The correlation between the average excess returns and the market betas is -0.24.

When we examine the betas on the 17 industry portfolios in Panel E, we find that neither the consumption beta nor the market beta explains the variation in average returns. For example, the market beta has a correlation of -0.17 with the average industry portfolio returns. The performance of the consumption beta is even worse. The correlation between the average excess returns and the consumption betas is -0.30.

In contrast, the electricity beta does a much better job in explaining the cross-sectional variation in the industry portfolio returns, arguably the biggest empirical challenge for many existing asset pricing models. The correlation between the average excess returns and the electricity betas is 0.48. Consumer product, food, and clothing industry portfolios have high electricity betas. These are the industries whose products require additional household production activities to yield final consumption utility (for example, meals and clean clothes). As captured by our electricity betas, these industries are more subject to household production risk and thus yield high returns on average. In contrast, industrial sectors, such as steel and fabricated (metal) products, are less subject to household production risk and therefore earn lower average returns. The utilities sector is one exception: It has a relatively high electricity beta but a low average return. This may be a result of the unusual features of utilities firms: Their returns may be mechanically related to electricity usage, and they are often regulated to earn a fair cost of capital.

As a graphical demonstration of the contribution of electricity growth to the asset pricing performance, we plot SMB and HML alongside electricity growth in Figure 4, and the excess log returns of the food, clothing, and consumer product industry portfolios alongside electricity growth in Figure 5. All these return series co-vary positively with electricity growth, and, again, the positive correlations are particularly strong for the food, clothing, and consumer product industry portfolios. This is consistent with the discussions above — for the size and book-to-market sorted portfolios, both the consumption and electricity betas vary and contribute to pricing performance. For the industry portfolios, electricity growth is arguably the only factor delivering the asset pricing results.

The ability of electricity growth to capture the cross-sectional variation in expected returns is what drives down the required risk-aversion parameter. To understand the underlying intuition, consider the standard additive power utility, which implies that expected spread portfolio returns (such as value and size premiums) are proportional to the product of the risk aversion and the covariance between electricity growth and spread portfolio returns. Since electricity growth comoves well with the HML and SMB returns, the covariance term is large. As a result, a lower risk aversion parameter is required for the model to explain the cross-sectional variation in expected returns.

To summarize, the success of our CE-EZ model arises from residential electricity growth's ability to capture the cross-sectional variation in stock returns' exposure to household production risk. This leads to a high R^2 as well as a low risk aversion in the estimation results.

4.4 Robustness analyses

We have proposed that residential electricity usage captures the service flow from household production capital in real time because it captures the fluctuation in household production activities due to varying use, even when the capital stock is held constant. As a result, one would expect electricity growth to perform better than the growth rate of household production capital in asset pricing tests. We show that is indeed the case in Table 6, where we replace residential electricity growth with the growth rate of the net stock of household appliances. We find that the asset pricing performance of the model deteriorates substantially. Risk aversion increases from 36 to 75 and R^2 drops from 71% to 47%. This result highlights the fact that the success of a household production model hinges on the accuracy of its empirical measures.

Our baseline estimation uses December-to-December electricity growth. While such a year-on-year growth rate calculation alleviates seasonalities coming from within-year weather fluctuations, it is still prone to across-year weather variations (e.g., this December is a lot colder than last December). To make sure that our results are not driven by this residual weather effect, we consider an adjustment in which we orthogonalize our benchmark residential electricity growth rates on the annual changes in December weather as measured by December heating degree days.[20] To the extent that colder days in December require more residential electricity usage for heating, this adjustment controls for the across-year weather effect. One caveat is that since the relationship between electricity usage and temperature is likely to be a complicated nonlinear function, our simple adjustment using a linear regression is not perfect and may introduce noise to our estimation. The pricing performance using this adjusted electricity growth is reported in Table 6. The key

[20]See Footnote 12 for more details on energy degree days. The weather effect explains about a third of the total variation in residential electricity growth, according to the R^2 of the regression of electricity growth on the EDD change.

finding is that the residual weather effect is not driving our results. Even after directly controlling for weather changes, residential electricity growth still performs well in the asset pricing tests. The pricing performance is slightly worse compared to our benchmark case, potentially due to the additional noise introduced by an arguably imperfect weather adjustment. In addition, unadjusted electricity growth may perform better because weather change may rationally affect asset pricing, as in Bansal and Ochoa (2012).

Savov (2011) argues that garbage is a better measure of consumption and shows that using garbage growth in standard CCAPM considerably reduces the risk aversion estimate. Using his garbage data, which cover the period of 1960–2007, to price the 25 Fama-French portfolios and the 17 industrial portfolios, we find a risk aversion of 32 and an R^2 of 34.1%. In comparison, our CE-EZ model estimated for the same sample period and on the same assets obtains a risk aversion of 39.2 and an R^2 of 67.9% .

Following Jagannathan and Wang (2007), our baseline estimation utilizes Q4-to-Q4 consumption growth, and, accordingly, December-to-December electricity growth, to price annual returns. As a robustness check, we also estimate CE-EZ model (both the log-linear factor model and the Euler equations) using all the data available. Specifically, we include overlapping, year-on-year growth rates sampled at a quarterly frequency: Q1-to-Q1, Q2-to-Q2, Q3-to-Q3, and Q4-to-Q4 consumption growth and March-to-March, June-to-June, September-to-September, and December-to-December electricity growth. The test assets are also overlapping March-to-March, June-to-June, September-to-September, and December-to-December returns. Existing studies often focus on non-overlapping data, which is, obviously, different from our approach. As discussed earlier, our approach minimizes the confounding effect of weather-induced seasonalities. In addition, it facilitates a direct comparison with the baseline estimation.

As shown in Table 7, for the CE-EZ model, when we use data from all quarters, the estimates of the factor prices, and consequently the risk aversion parameter, are somewhat higher. The pricing performance of the model also falls, with an R^2 of about 58%. Similarly, a decline in the asset pricing performance is also observed when we estimate the CE-Power model using data of all quarters. For comparison, we also report in Table 7 the all-quarter estimation results for C-Power and C-EZ, two models with consumption but without electricity. The results indicate substantial deterioration in the pricing performance: the R^2 becomes negative for C-Power, and is essentially zero for C-EZ.

Jagannathan and Wang (2007) found fourth quarter consumption growth rates to be more volatile than the year-on-year growth rates of the other three quarters; we also find that December-to-December electricity growth is the most volatile. In other words, the Q4-to-Q4 consumption growth and the December-to-December electricity growth indicate much higher risk than that reflected in annual growth data. Jagannathan and Wang (2007) attribute the difference to a calendar cycle effect. In the U.S., the fourth quarter and specifically December coincide with the end of the tax year and the Christmas holiday. This is when investors both feel the need and have more time to review their consumption and portfolio choice decisions, and, consequently, asset pricing models should perform better. It is worth noting that even with all quarter cycles included, the CE-EZ model still outperforms other consumption-based models. Compared to market consumption, our results appear to suggest that the calendar cycle effect is weaker on electricity usage.[21]

When we use data from all quarters, the number of observations in the sample quadruples. Comparing Panel A of Table 3, Panel A of Table 4, and the results using all quarters in Table 7, we find that the larger sample does not yield lower standard errors for the estimates. As discussed above, the lower volatilities of non-Q4 and non-December growth rates imply higher factor prices and risk aversion, and potentially higher standard errors. In addition, the data points are overlapping in the larger sample. Altogether, the quadrupled number of observations does not necessarily result in an improvement in the standard errors.

The factor betas presented in Table 5 suggest that the electricity beta does a better job than the consumption beta in explaining cross-sectional return variations. One may therefore wonder whether there is still a need to include standard NIPA consumption growth in the model. In other

[21] Møller and Rangvid (2011) show that Q3-to-Q4 consumption growth predicts the market risk premium. When we use Q3-to-Q4 consumption growth in the CCAPM, we obtain a large estimate of risk aversion well over 150. This is most likely due to the very low volatility of Q3-to-Q4 consumption growth, which spans across only one quarter (as compared to Q4-to-Q4 growth rates that span across one year). It seems that Q3-to-Q4 consumption growth improves return predictability, but not the cross-sectional asset pricing performance. When we use Q4-to-Q4 consumption growth but September-to-December electricity growth in the CE-EZ model, we obtain a risk aversion of 71 and an R^2 of 26%.

words, is electricity growth alone sufficient for delivering asset pricing results? To answer this question, in Table 8 we examine two models without consumption growth.

Excluding the standard NIPA consumption growth leads to interesting insights. While the required risk aversion is reduced from 36 in the CE-EZ model to 29 in the model with electricity growth as the single factor (E only) or even further down to 22 in the two-factor model with electricity growth and market returns (E-EZ), the cross-sectional pricing performance is considerably compromised. The R^2 drops from 71% in the CE-EZ model to 16% in the single-factor E model and 50% in the two-factor E-EZ model. Therefore, the inclusion of the standard consumption growth factor is necessary to achieve a better cross-sectional pricing fit. This conclusion is consistent with the empirical findings reported by Jagannathan and Wang (2007) and the economic premise underlying the theory of household production: A household derives utility from both market consumption and consumption goods produced at home.

Since the expenditure on electricity is a part of the standard NIPA consumption bundle (albeit a tiny fraction, less than 2% using the 2009 figure), and electricity is used in many consumption activities, it is not surprising that electricity growth and NIPA consumption growth are positively correlated (correlation = 0.309, as reported in Table 1). This gives rise to a potential concern that electricity growth is simply the standard NIPA consumption growth plus some random noise. While this argument does not accord well with the factor beta results reported in Table 5, we nevertheless address this concern directly in Table 9. Specifically, in the spirit of Kan and Zhang (1999), we simulate a "noise" factor as $\Delta\tilde{e} = a_0 + a_1\Delta c + a_2\Delta e + a_3 r_m + a_4\varepsilon, \varepsilon \sim N(0,1)$. The constants a_i are chosen to match the mean and the standard deviation of electricity growth, the correlations between electricity growth and consumption growth and the market return. In addition, the correlation between the simulated noise factor and the empirical electricity growth is zero. In other words, the noise factor closely resembles electricity growth in terms of basic statistical properties but by construction does not bring any additional information to the estimation. We simulate 10,000 such noise factors and for each simulation, we use the resulting noise factor to replace the true residential electricity growth factor in the GMM estimation. We report in Table 9 the means and the 5th and 95th percentiles of the key pricing results using the simulated noise factors. These simulation results are obtained under the null hypothesis that electricity growth contains no additional information. On average, the noise factor does poorly compared to actual electricity growth: With the noise factor, it requires a higher risk aversion (62 vs. 36) and results in a lower R^2 (60% vs. 71%). In particular, the 5th percentile of the risk aversion parameter is 38 with the noise factor, higher than 36 in the case of true electricity growth; the 95th percentile of the R^2 is 69% with the noise factor, lower than 71% in the case of true electricity growth. In other words, we can reject with a 95% confidence level the null hypothesis that electricity growth contains no additional information.

5 Concluding remarks

While consumption Euler equations have formed the foundation of empirical asset pricing, the standard consumption-based asset pricing model (CCAPM) based on these Euler equations has found little empirical support. Incorporating insights from the Beckerian framework of household production, we propose a simple extension of the CCAPM that incorporates a household production function.

We propose that residential electricity usage is a useful real-time proxy for the service flow from household production capital, as electricity is used in most modern-day household production activities and it cannot be easily stored. Residential electricity usage data allow us to conduct the first direct test of the asset pricing implications of the Beckerian household production model. Using U.S. data from 1955 to 2012, we show that a household production model explains the cross section of the expected stock returns with an R^2 of 71% and a low risk aversion of 36.

In addition to demonstrating the asset pricing performance of the household consumption Euler equations, our paper also illustrates the usefulness of electricity data in financial applications. High-frequency real time electricity data over different geographic areas could lead to further applications in finance and economics.[22] We leave this for future studies.

[22] As a recent example, Ferson and Lin (2012) use electricity usage across different states as the proxy for investor heterogeneity in a study of mutual fund performance.

Appendices

A Pricing kernel

The agent maximizes

$$U_t = \left((1-\delta)V_t^{1-\frac{1}{\psi}} + \delta \Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}] \Big)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right)^{\frac{1}{1-\frac{1}{\psi}}}, \qquad V_t = C_t^{1-\alpha} E_t^{\alpha}. \tag{27}$$

The agent is subject to the budget constraints:

$$C_t + P_t I_t + Z_t = W_t, \qquad W_{t+1} = Z_t(R_{f,t} + \omega_t' R_{t+1}^x). \tag{28}$$

Each period, given wealth W_t, the agent chooses market consumption goods C_t and purchases new household capital I_t. Market consumption is the numeraire, the price of household capital relative to market goods is P_t, and the agent is a price taker. The agent produces household goods following

$$E_t = \phi_t K_t, \tag{29}$$

where K_t is the stock of household capital and ϕ_t is the intensity of utilization. The household capital stock evolves following

$$K_t = (1-\eta_{t-1})K_{t-1} + I_t, \qquad \eta_{t-1} = \eta(\phi_{t-1}), \tag{30}$$

where the depreciation rate rises with the intensity of utilization. Thus, more intensive use of household capital increases household production today, but also accelerates the depreciation and lowers the potential household production tomorrow. The agent invests the savings, Z_t, in the risk-free asset $R_{f,t}$ and risky assets, denoted by an excess return vector R_{t+1}^x. The agent chooses a portfolio vector ω_t for the risky assets.

Plug in $C_t = W_t + (1-\eta(\phi_{t-1}))P_t K_{t-1} - P_t K_t - Z_t$. The state variables are W_t, K_{t-1}, and ϕ_{t-1}. The agent chooses savings and financial investments, new investment of household capital, and the intensity of housework. Hence, the control variables are Z_t, ω_t, K_t, and ϕ_t. The first order condition with respect to the savings Z_t yields

$$(1-\delta)V_t^{-\frac{1}{\psi}} \frac{\partial V_t}{\partial C_t} = \delta \Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}] \Big)^{\frac{\gamma-\frac{1}{\psi}}{1-\gamma}} \mathbf{E}_t \left[U_{t+1}^{-\gamma} \frac{\partial U_{t+1}}{\partial W_{t+1}} (R_{f,t} + \omega_t' R_{t+1}^x) \right]. \tag{31}$$

The first order condition with respect to K_t is

$$(1-\delta)V_t^{-\frac{1}{\psi}}\left(\frac{\partial V_t}{\partial C_t}P_t - \frac{\partial V_t}{\partial E_t}\frac{\partial E_t}{\partial K_t}\right) = \delta\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{\gamma-\frac{1}{\psi}}{1-\gamma}}\mathbf{E}_t\left[U_{t+1}^{-\gamma}\frac{\partial U_{t+1}}{\partial K_t}\right]. \tag{32}$$

The first order condition with respect to ϕ_t is

$$(1-\delta)V_t^{-\frac{1}{\psi}}\left(-\frac{\partial V_t}{\partial E_t}\frac{\partial E_t}{\partial \phi_t}\right) = \delta\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{\gamma-\frac{1}{\psi}}{1-\gamma}}\mathbf{E}_t\left[U_{t+1}^{-\gamma}\frac{\partial U_{t+1}}{\partial \phi_t}\right]. \tag{33}$$

The first order condition with respect to the portfolio ω_t yields

$$0 = \delta\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{\gamma-\frac{1}{\psi}}{1-\gamma}}\mathbf{E}_t\left[U_{t+1}^{-\gamma}\frac{\partial U_{t+1}}{\partial W_{t+1}}R_{t+1}^x\right]. \tag{34}$$

The envelope theorem implies that

$$\frac{\partial U_t}{\partial W_t} = U_t^{\frac{1}{\psi}}(1-\delta)V_t^{-\frac{1}{\psi}}\frac{\partial V_t}{\partial C_t}, \tag{35}$$

$$\frac{\partial U_t}{\partial K_{t-1}} = U_t^{\frac{1}{\psi}}(1-\delta)V_t^{-\frac{1}{\psi}}\frac{\partial V_t}{\partial C_t}(1-\eta_{t-1})P_t, \tag{36}$$

$$\frac{\partial U_t}{\partial \phi_{t-1}} = U_t^{\frac{1}{\psi}}(1-\delta)V_t^{-\frac{1}{\psi}}\frac{\partial V_t}{\partial C_t}\left(-\frac{\partial \eta_{t-1}}{\partial \phi_{t-1}}\right)P_tK_{t-1}. \tag{37}$$

These results suggest that,

$$1 = \mathbf{E}_t\left[M_{t+1}(R_{f,t}+\omega_t' R_{t+1}^x)\right], \qquad 0 = \mathbf{E}_t\left[M_{t+1}R_{t+1}^x\right], \tag{38}$$

in which the pricing kernel is

$$\begin{aligned}
M_{t+1} &= \frac{1}{(1-\delta)V_t^{-\frac{1}{\psi}}\frac{\partial V_t}{\partial C_t}}\delta\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{\gamma-\frac{1}{\psi}}{1-\gamma}}U_{t+1}^{-\gamma}\frac{\partial U_{t+1}}{\partial W_{t+1}} \\
&= \delta\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{\gamma-\frac{1}{\psi}}{1-\gamma}}U_{t+1}^{-\gamma}U_{t+1}^{\frac{1}{\psi}}\frac{V_{t+1}^{-\frac{1}{\psi}}\frac{\partial V_{t+1}}{\partial C_{t+1}}}{V_t^{-\frac{1}{\psi}}\frac{\partial V_t}{\partial C_t}} \\
&= \delta\left(\frac{\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{1}{1-\gamma}}}{U_{t+1}}\right)^{\gamma-\frac{1}{\psi}}\frac{V_{t+1}^{-\frac{1}{\psi}}\frac{\partial V_{t+1}}{\partial C_{t+1}}}{V_t^{-\frac{1}{\psi}}\frac{\partial V_t}{\partial C_t}}.
\end{aligned} \tag{39}$$

The price of the household capital is

$$P_t = \frac{\partial V_t}{\partial E_t}\frac{\partial E_t}{\partial K_t}\Big/\frac{\partial V_t}{\partial C_t} + (1-\eta_t)\mathbf{E}_t[M_{t+1}P_{t+1}] = Q_t + (1-\eta_t)\mathbf{E}_t[M_{t+1}P_{t+1}], \tag{40}$$

in which Q_t, the ratio between the marginal utilities of C_t and K_t, is the user cost of household capital.

From the budget constraints,

$$\begin{aligned}
&W_t + (1-\eta_{t-1})P_tK_{t-1} = C_t + P_tK_t + Z_t \\
&= C_t + Q_tK_t + (1-\eta_t)\mathbf{E}_t[M_{t+1}P_{t+1}]K_t + Z_t\mathbf{E}_t[M_{t+1}(R_{f,t} + \omega_t' R^x_{t+1})] \\
&= C_t + Q_tK_t + \mathbf{E}_t[M_{t+1}(W_{t+1} + (1-\eta_t)P_{t+1}K_t)].
\end{aligned} \tag{41}$$

Define

$$\mathcal{W}_t = W_t + (1-\eta_{t-1})P_tK_{t-1} \tag{42}$$

as also containing the value of the household capital stock, then it is the present value of the entire stream of $\{C_s + Q_sK_s\}_{s=t}^{\infty}$.

We conjecture that U_t is linear homogeneous in W_t and K_{t-1}. By Euler's homogeneous function theorem,

$$U_t = \frac{\partial U_t}{\partial W_t}W_t + \frac{\partial U_t}{\partial K_{t-1}}K_{t-1} = \frac{\partial U_t}{\partial W_t}(W_t + (1-\eta_{t-1})P_tK_{t-1}) \tag{43}$$

Hence,

$$\mathcal{W}_t = \frac{U_t}{\frac{\partial U_t}{\partial W_t}} = \frac{U_t}{U_t^{\frac{1}{\psi}}(1-\delta)V_t^{-\frac{1}{\psi}}\frac{\partial V_t}{\partial C_t}} \tag{44}$$

To verify, we use backward induction to show that it satisfies

$$\mathcal{W}_t = C_t + Q_tK_t + \mathbf{E}_t[M_{t+1}\mathcal{W}_{t+1}]. \tag{45}$$

Start from the right-hand side,

$$
\begin{aligned}
&\mathbf{E}_t[M_{t+1}\mathcal{W}_{t+1}] \\
&= \mathbf{E}_t\left[\delta\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{\gamma-\frac{1}{\psi}}{1-\gamma}} U_{t+1}^{-\gamma} U_{t+1}^{\frac{1}{\psi}} \frac{V_{t+1}^{-\frac{1}{\psi}} \frac{\partial V_{t+1}}{\partial C_{t+1}}}{V_t^{-\frac{1}{\psi}} \frac{\partial V_t}{\partial C_t}} \frac{U_{t+1}}{U_{t+1}^{\frac{1}{\psi}}(1-\delta)V_{t+1}^{-\frac{1}{\psi}} \frac{\partial V_{t+1}}{\partial C_{t+1}}}\right] \\
&= \frac{\delta}{1-\delta}\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{\gamma-\frac{1}{\psi}}{1-\gamma}} \frac{1}{V_t^{-\frac{1}{\psi}} \frac{\partial V_t}{\partial C_t}} \mathbf{E}_t[U_{t+1}^{1-\gamma}] \\
&= \frac{\delta\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}}{(1-\delta)V_t^{-\frac{1}{\psi}} \frac{\partial V_t}{\partial C_t}}.
\end{aligned}
\tag{46}
$$

That is,

$$
\mathbf{E}_t[M_{t+1}\mathcal{W}_{t+1}](1-\delta)V_t^{-\frac{1}{\psi}} \frac{\partial V_t}{\partial C_t} = \delta\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}. \tag{47}
$$

Second, also from the right-hand side,

$$
\begin{aligned}
&(C_t+Q_tK_t)(1-\delta)V_t^{-\frac{1}{\psi}} \frac{\partial V_t}{\partial C_t} \\
&= (1-\delta)V_t^{-\frac{1}{\psi}}\left(C_t\frac{\partial V_t}{\partial C_t} + K_t\frac{\partial V_t}{\partial E_t}\frac{\partial E_t}{\partial K_t}\right) = (1-\delta)V_t^{1-\frac{1}{\psi}}.
\end{aligned}
\tag{48}
$$

Here we have applied the result for Q_t and the definitions of V_t and E_t. Together, from the right-hand side,

$$
\begin{aligned}
&\Big(C_t+Q_tK_t+\mathbf{E}_t[M_{t+1}\mathcal{W}_{t+1}]\Big)(1-\delta)V_t^{-\frac{1}{\psi}} \frac{\partial V_t}{\partial C_t} \\
&= (1-\delta)V_t^{1-\frac{1}{\psi}} + \delta\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} = U_t^{1-\frac{1}{\psi}}.
\end{aligned}
\tag{49}
$$

This equals the left-hand side,

$$
\mathcal{W}_t(1-\delta)V_t^{-\frac{1}{\psi}} \frac{\partial V_t}{\partial C_t} = U_t^{1-\frac{1}{\psi}}. \tag{50}
$$

Use the above results,

$$
\mathcal{W}_t-(C_t+Q_tK_t) = \frac{U_t^{1-\frac{1}{\psi}}-(1-\delta)V_t^{1-\frac{1}{\psi}}}{(1-\delta)V^{-\frac{1}{\psi}} \frac{\partial V_t}{\partial C_t}} = \frac{\delta\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}}{(1-\delta)V^{-\frac{1}{\psi}} \frac{\partial V_t}{\partial C_t}}. \tag{51}
$$

Thus, for the total wealth return,

$$\frac{1}{R_{\mathcal{W},t+1}} = \frac{\mathcal{W}_t-(C_t+Q_tK_t)}{\mathcal{W}_{t+1}} = \frac{\delta\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}}{(1-\delta)V^{-\frac{1}{\psi}}\frac{\partial V_t}{\partial C_t}} \quad \frac{(1-\delta)V_{t+1}^{-\frac{1}{\psi}}\frac{\partial V_{t+1}}{\partial C_{t+1}}}{U_{t+1}^{1-\frac{1}{\psi}}}$$
$$= \delta\left(\frac{\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{1}{1-\gamma}}}{U_{t+1}}\right)^{1-\frac{1}{\psi}} \quad \frac{V_{t+1}^{-\frac{1}{\psi}}\frac{\partial V_{t+1}}{\partial C_{t+1}}}{V^{-\frac{1}{\psi}}\frac{\partial V_t}{\partial C_t}}. \tag{52}$$

Let $\theta=(1-\gamma)/(1-\frac{1}{\psi})$. Then,

$$R_{\mathcal{W},t+1}^{\theta-1} = \delta^{1-\theta}\left(\frac{\Big(\mathbf{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{1}{1-\gamma}}}{U_{t+1}}\right)^{(1-\frac{1}{\psi})(1-\theta)} \quad \left(\frac{V_{t+1}^{-\frac{1}{\psi}}\frac{\partial V_{t+1}}{\partial C_{t+1}}}{V^{-\frac{1}{\psi}}\frac{\partial V_t}{\partial C_t}}\right)^{1-\theta}. \tag{53}$$

Put into the pricing kernel,

$$M_{t+1} = \delta^{\theta}\left(\frac{V_{t+1}^{-\frac{1}{\psi}}\frac{\partial V_{t+1}}{\partial C_{t+1}}}{V^{-\frac{1}{\psi}}\frac{\partial V_t}{\partial C_t}}\right)^{\theta} R_{\mathcal{W},t+1}^{\theta-1}. \tag{54}$$

Since

$$V_t = C_t^{1-\alpha}E_t^{\alpha}, \qquad \frac{\partial V_t}{\partial C_t} = (1-\alpha)\left(\frac{E_t}{C_t}\right)^{\alpha}, \tag{55}$$

we obtain

$$M_{t+1} = \delta^{\theta}\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}-\alpha\theta(1-\frac{1}{\psi})} \left(\frac{E_{t+1}}{E_t}\right)^{\alpha\theta(1-\frac{1}{\psi})} R_{\mathcal{W},t+1}^{\theta-1}. \tag{56}$$

Hence, the wealth portfolio, $\mathcal{W}_t$, whose return appears in the pricing kernel, is expanded to include the value of the household capital stock.

Define market consumption wealth as the present value of the entire stream of market consumption,

$$G_t = C_t + \mathbf{E}_t[M_{t+1}G_{t+1}]. \tag{57}$$

Since

$$C_t + Q_t K_t = C_t + \left(\frac{\partial V_t}{\partial E_t}\frac{\partial E_t}{\partial K_t}\bigg/\frac{\partial V_t}{\partial E_t}\right) K_t = C_t + \frac{\alpha C_t^{1-\alpha} E_t^{\alpha-1}\phi_t}{(1-\alpha)C_t^{-\alpha}E_t^{\alpha}} K_t$$
$$= C_t + \frac{\alpha}{1-\alpha} C_t = \frac{1}{1-\alpha} C_t, \tag{58}$$

we obtain

$$G_t = (1-\alpha)\mathcal{W}_t, \qquad R_{g,t+1} = \frac{G_{t+1}}{G_t - C_t} = R_{\mathcal{W},t+1}. \tag{59}$$

The market consumption wealth is proportional to the total wealth, and the market consumption wealth return is equal to the total wealth return. Thus finally,

$$M_{t+1} = \delta^{\theta}\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}-\alpha\theta(1-\frac{1}{\psi})}\left(\frac{E_{t+1}}{E_t}\right)^{\alpha\theta(1-\frac{1}{\psi})} R_{g,t+1}^{\theta-1}. \tag{60}$$

B Pricing equation

The log pricing kernel is linear in the factors,

$$\log M_t = m_t = \mu_m - b_1\Delta c_t - b_2\Delta e_t - b_3 r_{g,t}. \tag{61}$$

Assume that the conditional distributions of the log pricing kernel, the log risk-free rate, and the log return are jointly normal. Then for the log risk-free rate,

$$\mathbf{E}_{t-1}[\exp(m_t + r_{f,t-1})] = 1, \tag{62}$$
$$\mathbf{E}_{t-1}[m_t + r_{f,t-1}] + \frac{1}{2}\operatorname{var}_{t-1}[m_t + r_{f,t-1}] = 0, \tag{63}$$
$$\mathbf{E}_{t-1}[m_t] + r_{f,t-1} + \frac{1}{2}\operatorname{var}_{t-1}[m_t] = 0. \tag{64}$$

For the log return,

$$\mathbf{E}_{t-1}[\exp(m_t + r_t)] = 1, \tag{65}$$
$$\mathbf{E}_{t-1}[m_t + r_t] + \frac{1}{2}\operatorname{var}_{t-1}[m_t + r_t] = 0, \tag{66}$$
$$\mathbf{E}_{t-1}[m_t] + \mathbf{E}_{t-1}[r_t] + \frac{1}{2}\operatorname{var}_{t-1}[m_t] + \frac{1}{2}\operatorname{var}_{t-1}[r_t] + \operatorname{cov}_{t-1}[m_t, r_t] = 0. \tag{67}$$

Subtract the two equations above,

$$\mathbf{E}_{t-1}[r_t - r_{f,t-1}] + \frac{1}{2}\operatorname{var}_{t-1}[r_t] + \operatorname{cov}_{t-1}[m_t, r_t] = 0. \tag{68}$$

There are equivalent ways to compute the conditional covariance:

$$\begin{aligned}\mathrm{cov}_{t-1}[m_t, r_t] &= \mathbf{E}_{t-1}[(m_t - \mathbf{E}_{t-1}[m_t])(r_t - \mathbf{E}_{t-1}[r_t])] \\ &= \mathbf{E}_{t-1}[(m_t - \mathbf{E}_{t-1}[m_t])(r_t - r_{f,t-1})]. \end{aligned} \tag{69}$$

In addition,

$$\mathrm{var}_{t-1}[r_t] = \mathrm{var}_{t-1}[r_t - r_{f,t-1}] \tag{70}$$

Hence,

$$\mathbf{E}_{t-1}[r_t - r_{f,t-1}] + \frac{1}{2}\,\mathrm{var}_{t-1}[r_t - r_{f,t-1}] = -\mathbf{E}_{t-1}[(m_t - \mathbf{E}_{t-1}[m_t])(r_t - r_{f,t-1})]. \tag{71}$$

Assume no conditional variations, then

$$\mathbf{E}[r_t - r_{f,t-1}] + \frac{1}{2}\,\mathrm{var}[r_t - r_{f,t-1}] = -\mathbf{E}[(m_t - \mu_m)(r_t - r_{f,t-1})]. \tag{72}$$

Since

$$m_t = \mu_m - (f_t - \mu_f)' b, \tag{73}$$

we have

$$\mathbf{E}[r_t^x] + \frac{1}{2}\,\mathrm{var}[r_t^x] = \mathbf{E}[r_t^x (f_t - \mu_f)'] b. \tag{74}$$

For CAPM and Fama-French factor models, the pricing kernel is

$$M_t = \mu_M - (f_t - \mu_f)' b, \tag{75}$$

which prices the risk-free rate and returns

$$\mathbf{E}[M_t R_{f,t-1}] = 1, \qquad \mathbf{E}[M_t R_t] = 1. \tag{76}$$

and the pricing equation is

$$\mathbf{E}[R_t^x] = \mathbf{E}[R_t^x (f_t - \mu_f)'] b. \tag{77}$$

C Factor betas

Factor betas are

$$\beta = \mathbf{E}[(f_t - \mu_f)(f_t - \mu_f)']^{-1}\,\mathbf{E}[(f_t - \mu_f)X_t'], \tag{78}$$

where $X_t = r_t^x$ for log-linear models and $X_t = R_t^x$ for linear models. Since

$$\text{var}[f_t] = \mathbf{E}[(f_t - \mu_f)(f_t - \mu_f)'], \tag{79}$$

and

$$\text{cov}[X_t, f_t] = \mathbf{E}[(X_t - \mathbf{E}[X_t])(f_t - \mu_f)'] = \mathbf{E}[X_t(f_t - \mu_f)'], \tag{80}$$

it follows that

$$\beta = \big(\text{var}[f_t]\big)^{-1}\text{cov}[X_t, f_t], \tag{81}$$

which are slope coefficients of regressing excess returns on factors.

D EIS

Our model implies a link between potential values of risk aversion γ and the EIS ψ. Using the relations between the prices of risk and the preference parameters in Eqs. (5) to (7), we obtain

$$\gamma = b_1 + b_2 + b_3,$$
$$\psi = \frac{1 - b_3}{b_1 + b_2},$$

which then implies

$$\psi = \frac{1 - b_3}{\gamma - b_3}.$$

In our results, the factor prices of risk are all positive (b_1, b_2, and b_3 for consumption growth, electricity growth, and the market return, respectively), which are economically reasonable since they imply positive factor risk premiums. In addition, we find large magnitudes for b_1 and b_2, while $b_3 < 1$. These estimates implies that $\gamma > 1$, which is arguably the consensus of the literature. Further, with $b_3 < 1$, they suggest that ψ is lower than $1/\gamma$, implying a preference for late resolution of uncertainty. Consistent with this relation, we estimate a very small $\psi = 0.0025$.

In our model, the linearized Euler equation is

$$r_{t+1} = g + b_1 \Delta c_{t+1} + b_2 \Delta e_{t+1} + b_3 r_{g,t+1} + h_{t+1}. \tag{82}$$

When we plug in the corresponding b_1, b_2, and b_3, we obtain

$$r_{t+1} = g + 21.2 \Delta c_{t+1} + 14.3 \Delta e_{t+1} + 0.911 r_{g,t+1} + h_{t+1}. \tag{83}$$

Thus, variations in Δc, going into r, are amplified by $b_1 = 21.2$, the effect of which, while still large, is arguably much less dramatic than implied by $1/\psi = 400$ in the case of power utility model.

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Table 1: Descriptive statistics. This table reports summary statistics for growth rates and market returns. The sample period is 1955–2012. Consumption growth is the Q4-to-Q4 growth rate of nondurable goods and services, electricity growth is the December-to-December growth rate of residential electricity usage, annual market return is from the CRSP, and $AC(1)$ is the first-order autocorrelation. Standard errors, presented in parentheses, are Newey-West corrected with two lags.

				Correlation	
	Mean (%)	Std Dev (%)	$AC(1)$	Consumption growth	Electricity growth
Consumption growth	1.98	1.42	0.397 (0.125)		
Electricity growth	2.99	5.68	-0.228 (0.198)	0.354 (0.083)	
Market return	7.26	17.35	-0.102 (0.112)	0.331 (0.100)	0.027 (0.110)

Table 2: Electricity growth, appliances growth, and housework hours growth. This table reports the relations between electricity growth, appliances growth, and housework hours growth. In Panel A, the sample period is 1955–2012, electricity growth is the December-to-December growth rate of residential electricity usage, and appliances growth is the growth rate of the year-end net stock of household appliances. In Panel B, the sample period is 2003–2012, electricity growth is the growth rate of annual residential electricity usage, and housework hours growth is the growth rate of the annual average hours of household activities. Standard errors, presented in parentheses, are Newey-West corrected with two lags.

A. Appliances growth and electricity growth (1955–2012)

Mean (%)	Std Dev (%)	Correlation with electricity growth	Regression of electricity growth on appliances growth		
			Intercept	Slope	R^2
3.02	1.86	0.297 (0.104)	0.0025 (0.0098)	0.906 (0.311)	0.088

B. Housework hours growth and electricity growth (2003–2012)

	Mean (%)	Std Dev (%)	Correlation with electricity growth	Regression of electricity growth on housework hours growth		
				Intercept	Slope	R^2
Housework hours growth	-0.52	2.77	0.304 (0.207)	0.0018 (0.0067)	0.326 (0.256)	0.092
Electricity growth	0.01	2.98				

Table 3: Estimation of factor models. This table reports factor risk prices and preference parameters estimated from factor models. In Panel A, the test assets are the annual returns of 25 Fama-French portfolios and 17 industry portfolios. In Panel B, the test assets are the annual returns of 25 Fama-French portfolios *only*. The sample period is 1955–2012. Consumption is fourth quarter nondurable goods and services, and electricity is December residential usage. For the CAPM, the factor is annual excess market return. For the Fama-French model, the factors are annual excess market return, SMB, and HML. For the C-Power model, the factor is log Q4-to-Q4 consumption growth. For the C-EZ model, the factors are log Q4-to-Q4 consumption growth and log annual market return. For the CE-Power model, the factors are log Q4-to-Q4 consumption growth and log December-to-December electricity growth. For the CE-EZ model, the factors are log Q4-to-Q4 consumption growth, log December-to-December electricity growth, and log annual market return. The preference parameters are computed from factor risk prices. The preference parameters are: risk aversion (γ), the elasticity of intertemporal substitution (ψ), and the share of electricity (α). Pricing error is the difference between realized and model-predicted average portfolio returns, MAPE is the mean absolute pricing error, and R^2 is 1 minus the ratio of the cross-sectional variance of the pricing errors to the cross sectional variance of realized average portfolio returns. Estimation is by two-step GMM. Standard errors, presented in parentheses, are Newey-West corrected with two lags. For R^2, 5th and 95th percentiles, presented in brackets, are obtained using bootstrap.

A. With Fama-French and industry portfolios

Factor/	Model					
Parameter	CAPM	Fama-French	C-Power	C-EZ	CE-Power	CE-EZ
Consumption			102.5	78.2	37.7	21.2
			(7.97)	(8.20)	(5.00)	(4.61)
Electricity					18.9	14.3
					(1.61)	(1.19)
Market	2.72	2.68		0.071		0.911
	(0.30)	(0.39)		(0.240)		(0.220)
SMB		0.250				
		(0.641)				
HML		3.42				
		(0.48)				
γ			102.5	78.3	56.7	36.4
			(7.97)	(8.11)	(6.10)	(4.35)
ψ				0.0119		0.0025
				(0.0028)		(0.0061)
α					0.341	0.404
					(0.025)	(0.060)
MAPE	2.22%	1.58%	1.68%	1.64%	1.29%	1.09%
R^2	-29.5%	34.5%	16.6%	23.7%	48.6%	71.1%
	[-44.6%, 24.6%]	[5.1%, 62.8%]	[-11.5%, 47.1%]	[-2.1%, 54.2%]	[9.1%, 61.8%]	[16.3%, 80.4%]

B. With Fama-French portfolios *only*

Factor/ Parameter	Model					
	CAPM	Fama-French	C-Power	C-EZ	CE-Power	CE-EZ
Consumption			106.0	105.3	49.3	26.9
			(14.8)	(23.9)	(13.8)	(13.1)
Electricity					22.0	16.0
					(3.82)	(2.94)
Market	2.76	2.61		-0.727		0.702
	(0.47)	(0.52)		(0.943)		(0.530)
SMB		0.81				
		(1.03)				
HML		4.02				
		(0.85)				
γ			106.0	104.6	71.3	43.6
			(14.8)	(23.2)	(15.8)	(12.2)
ψ				0.0164		0.0069
				(0.0069)		(0.0110)
α					0.313	0.375
					(0.057)	(0.132)
MAPE	2.52%	1.11%	1.23%	1.18%	1.13%	0.94%
R^2	-38.5%	65.2%	55.0%	63.8%	71.1%	85.8%
	[-54.4%, 18.0%]	[26.5%, 84.1%]	[14.1%, 67.7%]	[18.8%, 77.4%]	[27.7%, 82.1%]	[35.4%, 90.5%]

Table 4: Preference parameters estimated from Euler equations. This table reports the preference parameters estimated from the pricing kernel in the Euler equations. In Panel A, the test assets are the annual returns of 25 Fama-French portfolios and 17 industry portfolios. In Panel B, the test assets are the annual returns of 25 Fama-French portfolios *only*. The sample period is 1955–2012. Consumption is fourth quarter nondurable goods and services, and electricity is December residential usage. The C-Power model is consumption in power utility. The C-EZ model is consumption in Epstein-Zin preferences. The CE-Power model is a Cobb-Douglas function of consumption and electricity embedded in power utility. The CE-EZ model is a Cobb-Douglas function of consumption and electricity embedded in Epstein-Zin preferences. The preference parameters are: the time discount factor (δ), risk aversion (γ), the elasticity of intertemporal substitution (ψ), and the share of electricity (α). Estimation is by two-step GMM. Standard errors, presented in parentheses, are Newey-West corrected with two lags.

Parameter	Model			
	C-Power	C-EZ	CE-Power	CE-EZ
A. With Fama-French and industry portfolios				
β	0.935	0.932	0.938	0.930
	(0.146)	(0.486)	(0.125)	(0.528)
γ	102.6	79.2	55.5	37.0
	(8.60)	(8.88)	(7.72)	(8.56)
ψ		0.0042		0.0078
		(0.0050)		(0.0101)
α			0.351	0.415
			(0.062)	(0.110)
B. With Fama-French portfolios *only*				
δ	0.920	0.933	0.928	0.936
	(0.181)	(0.135)	(0.198)	(0.420)
γ	109.2	115.8	67.6	47.8
	(11.0)	(11.9)	(12.9)	(14.9)
ψ		0.0125		0.0125
		(0.0040)		(0.0105)
α			0.338	0.403
			(0.081)	(0.146)

Table 5: Factor betas implied by the GMM estimation of the CE-EZ log-linear factor model. This table reports the average adjusted excess log returns of test assets and the factor betas implied by the GMM estimation of the CE-EZ log-linear factor model. The test assets are the annual returns of 25 Fama-French portfolios and 17 industry portfolios. The sample period is 1955–2012. Consumption is fourth quarter nondurable goods and services, and electricity is December residential usage. In the CE-EZ model, the factors are log Q4-to-Q4 consumption growth, log December-to-December electricity growth, and log annual market return. Panels A to D report the results for 25 Fama-French portfolios. Panel E reports the results for 17 industry portfolios, in which the industries are sorted by average adjusted excess log return.

A. Average adjusted excess log returns of 25 Fama-French portfolios (%)

	Book-to-market equity				
Size	Low	2	3	4	High
Small	4.72	9.89	10.08	12.10	14.02
2	5.84	8.67	10.64	11.12	12.12
3	6.04	9.03	8.91	10.76	11.97
4	7.03	6.80	8.76	10.05	9.97
Big	5.50	5.95	6.39	6.24	7.61

B. Betas of 25 Fama-French portfolios on consumption growth

	Book-to-market equity				
Size	Low	2	3	4	High
Small	5.49	6.13	5.44	5.79	6.92
2	4.21	4.26	5.39	6.01	6.61
3	4.03	5.22	4.55	5.39	5.69
4	3.62	4.18	5.49	6.06	6.88
Big	3.98	3.47	4.51	5.23	5.54

C. Betas of 25 Fama-French portfolios on electricity growth

	Book-to-market equity				
Size	Low	2	3	4	High
Small	0.08	0.50	0.63	0.93	0.92
2	0.07	0.53	0.91	0.92	1.05
3	0.11	0.72	0.83	1.10	1.05
4	0.31	0.55	0.77	0.99	0.73
Big	0.21	0.34	0.42	0.49	0.35

D. Betas of 25 Fama-French portfolios on market return

	Book-to-market equity				
Size	Low	2	3	4	High
Small	1.50	1.30	1.07	0.94	1.12
2	1.32	1.06	0.96	0.93	0.97
3	1.21	1.01	0.84	0.95	0.86
4	1.10	0.94	0.96	0.94	1.07
Big	0.98	0.84	0.81	0.86	0.95

E. 17 industry portfolios

	Average adjusted excess log return (%)	Beta		
		Consumption	Electricity	Market
Steel	3.87	6.19	0.32	1.07
Utils	5.98	3.02	0.56	0.64
FabPr	6.00	3.88	0.33	0.76
Chems	6.05	3.56	0.37	0.92
Other	6.08	3.72	0.03	1.01
Durbl	6.19	4.05	0.16	1.07
Cnstr	6.63	4.00	0.03	1.02
Trans	6.64	4.45	0.63	0.94
Finan	6.84	5.81	0.84	1.02
Cars	7.06	6.33	0.13	1.23
Machn	7.68	5.76	0.31	1.18
Oil	7.75	4.80	0.81	0.68
Mines	7.84	3.46	0.63	0.84
Rtail	8.03	4.17	0.28	1.04
Clths	8.43	4.89	0.72	1.14
Food	8.46	2.97	0.73	0.73
Cnsum	8.99	2.54	0.78	0.68

Table 6: Variants of the CE-EZ model. This table reports the estimation of two variants of the CE-EZ model. The test assets are the annual returns of 25 Fama-French portfolios and 17 industry portfolios. The sample period is 1955–2012. For the "Appliances" columns, the estimation employs Q4-to-Q4 log growth rates of nondurable goods and services and annual log growth rates of year-end net stock of household appliances. For the "Adjusted E" columns, the estimation employs Q4-to-Q4 log growth rates of nondurable goods and services and residuals of December-to-December log growth rates of residential electricity usage regressed on December-to-December changes in weather as measured by heating degree days. The "LFM" columns present the factor risk prices and the preference parameters estimated from the log-linear factor model. The factors are log consumption growth, log electricity (or appliances) growth, and with (or without) log market return. The preference parameters are computed from the factor risk prices. Pricing error is the difference between realized and model-predicted average portfolio returns, MAPE is the mean absolute pricing error, and R^2 is 1 minus the ratio of the cross-sectional variance of the pricing errors to the cross sectional variance of realized average portfolio returns. The "Pref" column presents the preference parameters estimated from the pricing kernel in the Euler equations. The model is a Cobb-Douglas function of consumption and electricity (or appliances) embedded in Epstein-Zin (or power) utility. The preference parameters are: the time discount factor (δ), risk aversion (γ), the elasticity of intertemporal substitution (ψ), and the share of electricity (or appliances) (α). Estimation is by two-step GMM. Standard errors, presented in parentheses, are Newey-West corrected with two lags. For R^2, 5th and 95th percentiles, presented in brackets, are obtained using bootstrap.

Factor/	Appliances		Adjusted E	
Parameter	LFM	Pref	LFM	Pref
Consumption	47.6		31.4	
	(6.59)		(7.88)	
Electricity	26.7		22.3	
	(2.48)		(1.87)	
Market	1.099		1.214	
	(0.191)		(0.508)	
δ		0.943		0.940
		(0.598)		(0.599)
γ	75.4	80.3	54.9	52.8
	(7.48)	(11.5)	(7.90)	(8.72)
ψ	-0.0013	-0.0061	-0.0040	-0.0037
	(0.0026)	(0.0062)	(0.0097)	(0.0076)
α	0.359	0.388	0.414	0.424
	(0.034)	(0.109)	(0.061)	(0.087)
MAPE	1.30%		1.10%	
R^2	47.3%		68.3%	
	[7.7%, 60.7%]		[19.6%, 73.5%]	

Table 7: Estimation using the data for all quarters. This table reports the estimation of various models using the data for all quarters. The test assets are 25 Fama-French portfolios and 17 industry portfolios. The sample period is 1955–2012. The estimation employs overlapping March-to-March, June-to-June, September-to-September, and December-to-December returns, overlapping Q1-to-Q1, Q2-to-Q2, Q3-to-Q3, and Q4-to-Q4 log growth rates of nondurable goods and services, and overlapping March-to-March, June-to-June, September-to-September, and December-to-December log growth rates of residential electricity usage. The "LFM" columns present the factor risk prices and the preference parameters estimated from the log-linear factor model. For the C-Power model, the factor is log consumption growth. For the C-EZ model, the factors are log consumption growth and log market return. For the CE-Power model, the factors are log consumption growth and log electricity growth. For the CE-EZ model, the factors are log consumption growth, log electricity growth, and log market return. The preference parameters are computed from the factor risk prices. Pricing error is the difference between realized and model-predicted average portfolio returns, MAPE is the mean absolute pricing error, and R^2 is 1 minus the ratio of the cross-sectional variance of the pricing errors to the cross sectional variance of realized average portfolio returns. The "Pref" column presents the preference parameters estimated from the pricing kernel in the Euler equations. The C-Power model is consumption in power utility. The C-EZ model is consumption in Epstein-Zin preferences. The CE-Power model is a Cobb-Douglas function of consumption and electricity embedded in power utility. The CE-EZ model is a Cobb-Douglas function of consumption and electricity embedded in Epstein-Zin preferences. The preference parameters are: the time discount factor (δ), risk aversion (γ), the elasticity of intertemporal substitution (ψ), and the share of electricity (α). Estimation is by two-step GMM. Standard errors, presented in parentheses, are Newey-West corrected with 8 lags. For R^2, 5th and 95th percentiles, presented in brackets, are obtained using bootstrap.

Factor/	C-Power		C-EZ		CE-Power		CE-EZ	
Parameter	LFM	Pref	LFM	Pref	LFM	Pref	LFM	Pref
Consumption	107.6		83.1		51.8		32.9	
	(10.1)		(9.18)		(10.6)		(8.94)	
Electricity					29.6		25.4	
					(3.84)		(2.97)	
Market			0.362				0.519	
			(0.277)				(0.413)	
δ		0.929		0.923		0.924		0.928
		(0.172)		(0.310)		(0.186)		(0.382)
γ	107.6	107.2	83.5	83.0	81.4	81.8	58.8	59.2
	(10.1)	(10.6)	(9.08)	(10.5)	(12.6)	(11.0)	(9.55)	(10.5)
ψ			0.0087	0.0078			0.0083	0.0082
			(0.0035)	(0.0048)			(0.0067)	(0.0071)
α					0.368	0.366	0.439	0.432
					(0.046)	(0.053)	(0.070)	(0.083)
MAPE	1.99%		1.92%		1.43%		1.12%	
R^2	-7.9%		3.0%		35.7%		57.9%	
	[-24.1%, 30.4%]		[-21.5%, 35.1%]		[4.1%, 57.2%]		[16.0%, 68.8%]	

Table 8: Models without consumption growth. This table reports the estimation of two models without consumption growth. The test assets are the annual returns of 25 Fama-French portfolios and 17 industry portfolios. The sample period is 1955–2012. Electricity is December residential usage. The "LFM" columns present the factor risk prices and the preference parameters estimated for the log-linear factor model. For the E only model, the factor is log December-to-December electricity growth. For the E-EZ model, the factors are log December-to-December electricity growth and log annual market return. The preference parameters are computed from the factor risk prices. Pricing error is the difference between realized and model-predicted average portfolio returns, MAPE is the mean absolute pricing error, and R^2 is 1 minus the ratio of the cross-sectional variance of the pricing errors to the cross sectional variance of realized average portfolio returns. The "Pref" columns present the preference parameters estimated from the pricing kernel in the Euler equations. The E only model is electricity in power utility. The E-EZ model is electricity in Epstein-Zin preferences. The preference parameters are: the time discount factor (δ), risk aversion (γ), and the elasticity of intertemporal substitution (ψ). Estimation is by two-step GMM. Standard errors, presented in parentheses, are Newey-West corrected with two lags. For R^2, 5th and 95th percentiles, presented in brackets, are obtained using bootstrap.

Factor/	E only		E-EZ	
Parameter	LFM	Pref	LFM	Pref
Electricity	29.2		20.1	
	(1.63)		(1.54)	
Market			1.705	
			(0.140)	
δ		0.929		0.935
		(0.027)		(0.040)
γ	29.2	30.0	21.8	21.3
	(1.63)	(1.47)	(1.53)	(1.43)
ψ			-0.0350	-0.0338
			(0.0077)	(0.0163)
MAPE	1.69%		1.36%	
R^2	16.2%		49.6%	
	[-17.7%, 37.6%]		[10.0%, 64.7%]	

Table 9: The CE-EZ model with a "noise" factor. This table reports the estimation of the CE-EZ log-linear factor model with the electricity factor replaced by a simulated noise factor. The test assets are the annual returns of 25 Fama-French portfolios and 17 industry portfolios. The sample period is 1955–2012. Consumption is fourth quarter nondurable goods and services, and electricity is December residential usage. The simulated noise factor is $\Delta\tilde{e} = a_0 + a_1\Delta c + a_2\Delta e + a_3 r_m + a_4\varepsilon, \varepsilon \sim N(0,1)$. The constants a_i are chosen to match the mean and the standard deviation of electricity growth and the correlations between electricity growth and consumption growth and market return. In addition, the correlation between the simulated noise factor and true electricity growth is zero. In the model, the factors are log Q4-to-Q4 consumption growth, the noise factor, and log annual market return. The preference parameters are computed from the factor risk prices. The preference parameters are: risk aversion (γ), the elasticity of intertemporal substitution (ψ), and the share of electricity (α). Pricing error is the difference between realized and model-predicted average portfolio returns, and R^2 is 1 minus the ratio of the cross-sectional variance of the pricing errors to the cross sectional variance of realized average portfolio returns. Estimation is by two-step GMM. The averages and percentiles of the estimated preference parameters and R^2 across 10,000 simulations are reported.

	Simulation		
Parameter	Mean	5%	95%
γ	61.6	37.6	77.3
ψ	0.0034	-0.0138	0.0188
α	0.153	0.020	0.384
R^2	59.9%	44.5%	68.7%

Figure 1: Seasonality of residential electricity usage. The top panel plots the time-series average of normalized residential electricity usage for each month over the period 1955–2012. Electricity usage data are obtained from the Energy Information Administration (EIA). Each year, we normalize monthly electricity usage by subtracting the mean and dividing by the standard deviation. Then for each month of a year, we compute the time-series average over the sample period. The bottom panel plots the the time-series average of normalized energy degree days (EDD) for each month over the same period. EDDs are the sum of cooling degree days (CDD) and heating degree days (HDD), which measure summer and winter weather variation, respectively. See footnote 12 for more details. The data on CDD and HDD are obtained from the National Oceanographic and Atmospheric Administration (NOAA). Each year, we normalize monthly CDDs and HDDs by subtracting the means and dividing by the standard deviations. Then for each month of a year, we compute the time-series averages over the sample period.

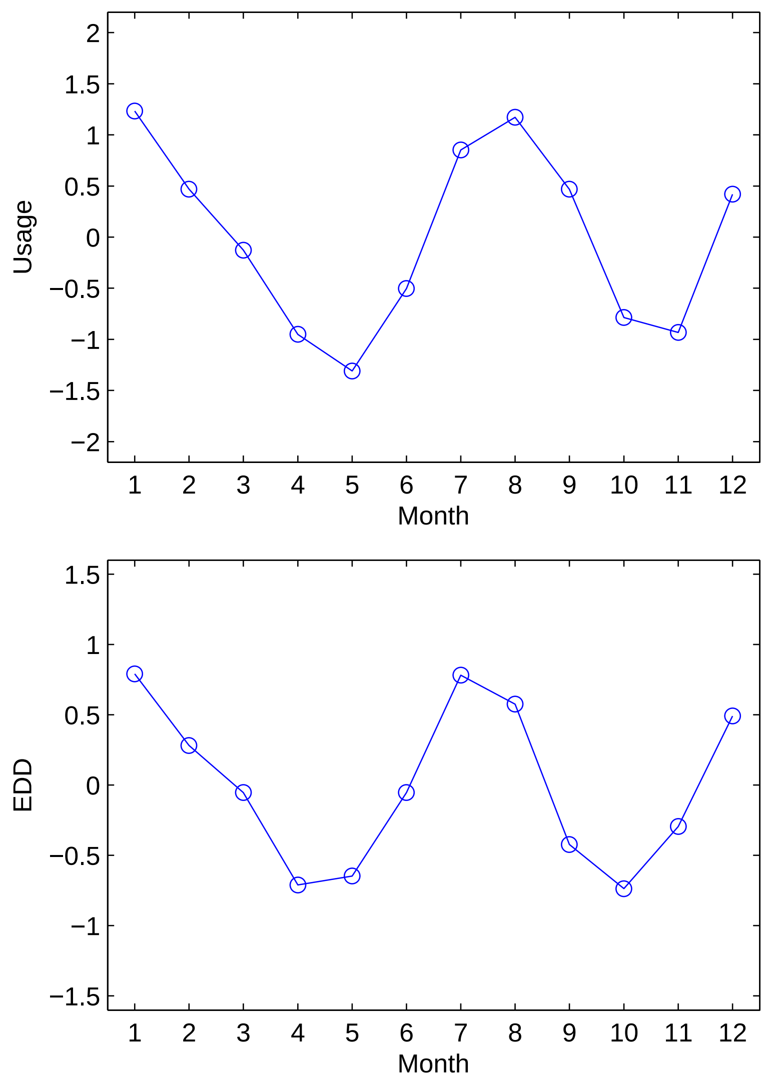


Figure 2: Electricity growth. The top panel plots December-to-December residential electricity growth and the Q4-to-Q4 growth rate of NIPA nondurable goods and services. The middle panel plots December-to-December residential electricity growth and the annual growth rate of the year-end net stock of household appliances. Shaded bars indicate NBER recessions. The sample period is 1955–2012 and thus growth rates are plotted for 1956–2012. The bottom panel plots annual residential electricity growth and the annual growth rate of the average hours of household activities. The sample period is 2003–2012 and thus growth rates are plotted for 2004–2012.

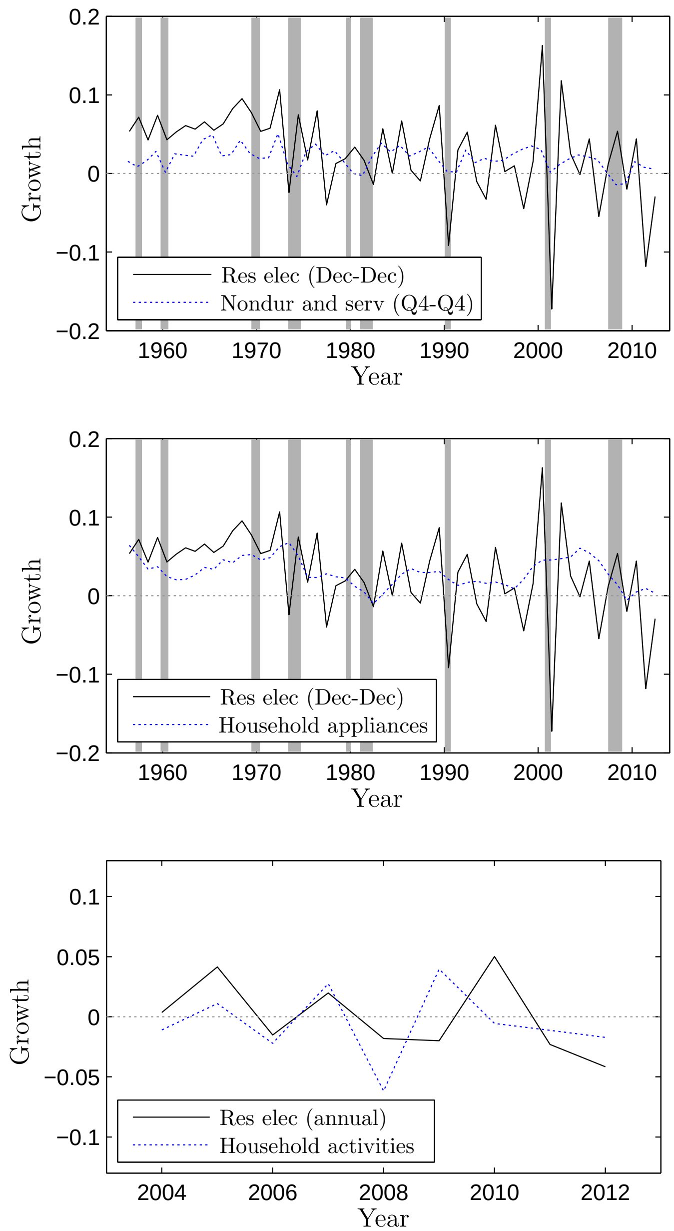
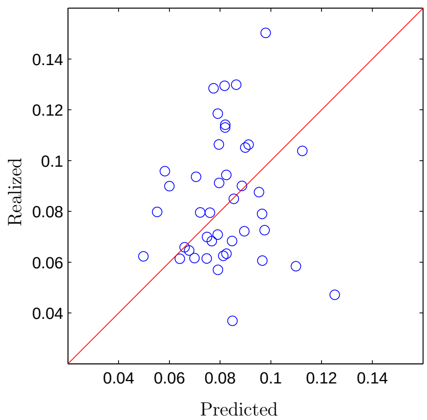
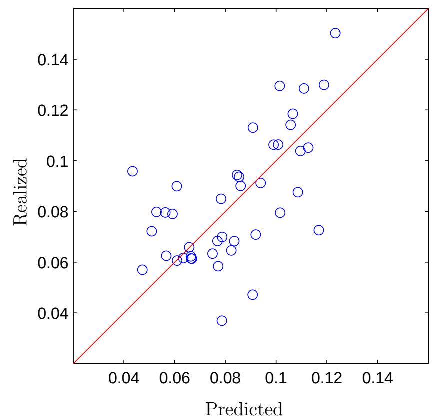


Figure 3: Realized and predicted average portfolio returns. This figure plots the model-predicted versus the realized average portfolio returnss. The test assets are the annual returns of 25 Fama-French portfolios and 17 industry portfolios. The sample period is 1955–2012. Consumption is fourth quarter nondurable goods and services, and electricity is December residential usage. The models are linear or log-linear factor models. For the CAPM, the factor is the annual excess market return. For the Fama-French model, the factors are the annual excess market return, SMB, and HML. For the C-Power, the factor is log Q4-to-Q4 consumption growth. For the C-EZ model, the factors are log Q4-to-Q4 consumption growth and log annual market return. For the CE-Power model, the factors are log Q4-to-Q4 consumption growth and log December-to-December electricity growth. For the CE-EZ model, the factors are log Q4-to-Q4 consumption growth, log December-to-December electricity growth, and log annual market return.

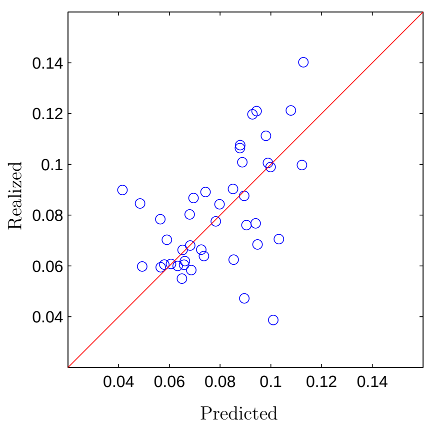
(a) CAPM



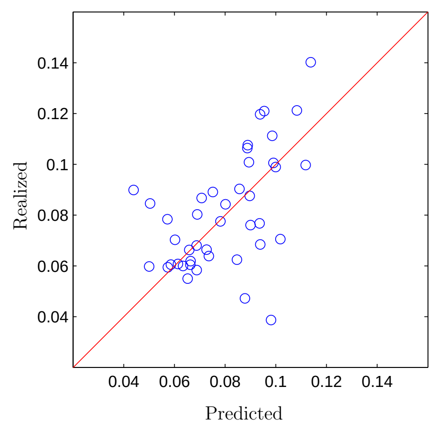
(b) Fama-French



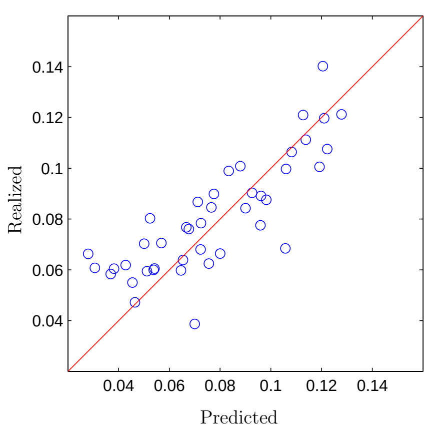
(c) C-Power



(d) C-EZ



(e) CE-Power



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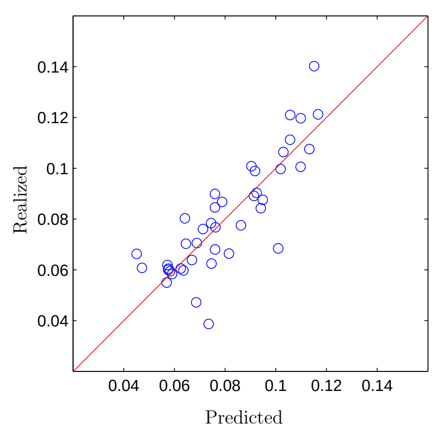

Figure 4: SMB and HML factors and electricity growth. Annual SMB and HML factors are plotted in solid lines to the scale on the left vertical axis. December-to-December electricity growth is plotted in dotted lines to the scale on the right vertical axis. The sample period is 1955–2012 and thus the factors and electricity growth are plotted for 1956–2012.

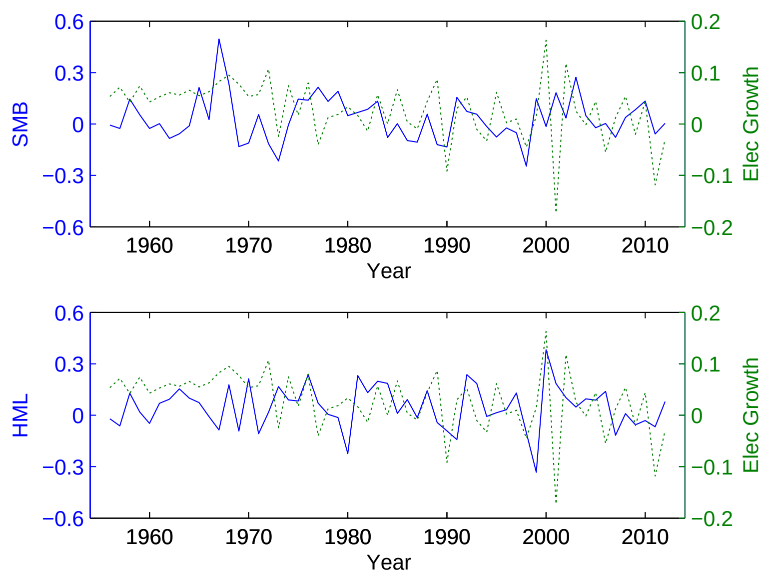

Figure 5: Industry portfolio returns and electricity growth. Annual excess log returns of the consumer product, food, and clothing industry portfolios are plotted in solid lines to the scale on the left vertical axis. Electricity growth is plotted in dotted lines to the scale on the right vertical axis. The sample period is 1955–2012 and thus the returns and electricity growth are plotted for 1956–2012.