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Non-Substitutable Consumption Growth Risk

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Abstract

Standard applications of the consumption-based asset pricing model assume that goods and services within the nondurable consumption bundle are substitutes. We estimate substitution elasticities between different consumption bundles and show that households cannot substitute energy consumption by consumption of other nondurables. As a consequence, energy consumption affects the pricing function as a separate factor. Variation in energy consumption betas explains a large part of the premia related to value, investment, and operating profitability. For example, value stocks are typically more energy-intensive than growth stocks and thus riskier, since they suffer more from the oil supply shocks that also affect households.

Keywords: Asset pricing, consumption, cross-section of stock returns

JEL: G12, E44, D81

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1 Introduction

Empirical implementations of the canonical asset pricing model of Lucas (1978) have largely focused on a definition of consumption as real consumption of nondurable goods and services. The evidence accumulated over the past 40 years suggests that it is difficult to reconcile observed asset pricing moments with the intertemporal marginal rate of substitution (IMRS) implied by constant relative risk aversion utility over i.i.d. growth in this measure of consumption. Cochrane (2017) discusses several theoretical attempts to resolve this discrepancy, which he notes generally augment the standard time-separable utility function with another variable, such as external habit in Campbell and Cochrane (1999). This variable does most of the work in resolving asset pricing moments with the model IMRS.

In this paper, we take an alternative approach and ask whether the consumption model fails in part because of the decision to treat nondurable goods and services consumption as a single bundle of consumption flows. Using granular consumption data, we find that some non-durable consumption goods should be conceived as complements to rather than substitutes for other nondurables. This finding has important asset pricing implications, since an augmented Lucas model with nonsubstitutable consumption goods implies that the growth rate of individual goods appear as separate factors in the pricing function. A counterfactual aggregation of complementary nondurable goods, in contrast, leads to important variation in individual nondurable goods being masked.

Why is nonsubstitutability so important for asset prices? In the spirit of the Lucas tree economy, imagine that there are two kinds of fruit growing in a garden. If the agent likes the two types equally and is always willing to trade one kind for the other, we can say that the two types are perfect substitutes for each other. In this case, we can simply look at the total quantity of fruit and conclude that the agent has a high marginal utility of consumption in states where this total number is low. In contrast, imagine that the first type of fruit is toxic. The second type contains an antidote, but is otherwise useless. The agent can only eat combinations of the two, and growing more of only one type provides no additional benefit. Consequently, the total quantity of fruit is not indicative of the agent's marginal utility. Even if this total quantity is high, the agent may be hungry because of a shortage in a complementary good.

In our empirical analysis, we find that energy goods are not substitutable by food and other nondurable goods. As a consequence, our model implies that agents seek to hold assets in their portfolios that provide insurance against states in which energy consumption is low. A prime example of such a scenario is the oil crisis in 1973 where households suffered from major shortages in energy products. Note that there was no shortage of food or other nondurable goods but the inability of households to substitute the missing energy goods by other goods led to high marginal utility in this situation.

Which assets are particularly sensitive to nonsubstitutable energy consumption growth shocks? We argue that firms, whose business models heavily depend on energy as an input factor, suffer from the scarcity of energy goods in exactly the same periods as households. This makes their equity particularly risky from the perspective of households. We show that firm-specific energy intensity is cross-sectionally correlated with standard risk measures such as the book-to-market ratio, profitability, and investments. These patterns explain why exposures to energy consumption risk are much more informative than aggregate consumption growth exposures when it comes to explaining cross-sectional variation in expected stock returns. The estimation of a linearized version of our model shows that the price of energy consumption risk is approximately 2% per quarter and explains 45% of the cross-sectional variation in average returns on 75 size, value, investment, and profitability-sorted portfolios. In contrast, models that do not separately account for energy consumption explain less than 10% of this variation.

Before analyzing the explanatory power for the cross-sectional return variation in a linearized version of our model, we also consider the nonlinear version to understand whether nonsubstitutability is also helpful in solving the equity premium puzzle. To do so, we estimate the model with GMM and find, however, that generalizing intertemporal preferences away from time-additive utility to recursive utility plays a more important role here. This result is consistent with earlier findings of Vissing-Jørgensen and Attanasio (2003), Bansal and Yaron (2004), and Chen et al. (2013).

Our focus on the importance of substitutes and complements in the components of consumption builds upon Dunn and Singleton (1986), Eichenbaum and Hansen (1990), Ogaki and Reinhart (1998), Yogo (2006), and Pakoš (2011) who show the importance of considering the service flow of durable goods in measuring consumption growth and risk premia. Yogo shows that the standard practice of omitting durable goods in measuring aggregate consumption under the assumption of separability contributes substantially to the failure of the consumption-based model. Uhlig (2010) and Cochrane (2017) point out that this assumption is no longer valid under the assumption of nonseparable utility, and we consider durable goods service flow in our analysis. However, our paper goes one step further and questions the assumption of substitutability *within* the set of nondurable goods and services, which is commonly used as a measure of aggregate consumption. Our findings demonstrate that *any* consumption flow that cannot be treated as a substitute for other goods in the consumption bundle has the potential to impact asset prices. Obviously, this point suggests that an even finer dissection of the consumption data into its components may reveal further imperfect substitution elasticities that are important for asset prices. Our focus in this paper is on a relatively coarse definition of the components of consumption to show that this elasticity matters. However, further investigation is a interesting question for future research.

We do not approach the question of which components of consumption are substitutes and complements with energy expenditures in mind. Rather, we consider energy consumption separately based on the empirical results regarding substitutability between the components of consumption. That said, it is not surprising that energy consumption is important for asset prices given earlier empirical evidence. In particular, Da et al. (2016) find that household electricity usage is an important factor for explaining the cross-sectional variation in expected stock returns. They argue that electricity usage serves as a proxy for household production of consumption goods, which is otherwise difficult to measure. Since electricity consumption is part of the consumption of energy in the NIPA tables, one would expect based on their results to find that energy consumption is important for explaining cross-sectional variation in average returns.

We estimate prices of risk in a linearized model that incorporates both consumption of electricity and NIPA energy consumption. Our results suggest that both measures have independent information for understanding the cross-section of returns, bearing positive and statistically significant prices of risk. This result might initially seem surprising as the NIPA energy consumption data includes expenditures on electricity in addition to goods such as gasoline and natural gas. We speculate that the electricity expenditures data are better measured but less broad than the NIPA data. Thus, while electricity consumption reflects the risks inherent in the household production function, consumption of other energy products also impacts marginal utility. Through the lens of our modeling framework, this impact arises from an inability of consumers to substitute other goods for energy when there are shocks to supply. As a result, consumption of energy bears a risk premium in asset markets.

In addition to these two papers, our work is related to several strands of the asset pricing literature. First, this study builds upon papers that examine consumption-based asset pricing models' ability to explain cross-sectional variation in returns (see, e.g., Lettau and Ludvigson, 2001; Parker and Julliard, 2005; Bansal et al., 2005; Yogo, 2006; Jagannathan and Wang, 2007; Hansen et al., 2008; Bansal et al., 2009; Boguth and Kuehn, 2013; Dittmar and Lundblad, 2017). We depart from this literature by starting from disaggregated elements of the total consumption flow, rather than assuming that nondurables and services represent a single bundle. Our results indicate that energy consumption should be separated, and represents an important source of consumption risk for asset pricing.

Second, as mentioned above, our paper complements research into models of asset prices with multiple goods. In contrast to these papers, we allow the data to inform us as to how to optimally bundle consumption, and find that the implications of this bundling for preferences profoundly changes our inferences about asset pricing. Baker and Routledge (2017) consider a two-good economy with a general consumption good and oil and investigate the implications for oil derivatives prices.

A third line of research investigates the role that oil prices play in asset pricing. Kilian and Park (2009) disentangle demand and supply shocks in oil prices with a VAR, and examine the impact of oil price shocks on asset prices. Ready (2018) argues that returns on firms from the oil producing sector in the U.S. can be used to identify supply and demand shocks separately and finds that supply-driven oil price changes are negatively related to asset returns, while the opposite is true for demand shocks. Gao et al. (2022) demonstrate the impact of oil volatility on asset prices when firms hold precautionary oil inventories. Finally, Fang et al. (2021) disentangle prices of core and energy inflation risk, and show that the latter is zero. This literature focuses on oil prices, while we utilize the quantity of energy consumed by households.

In addition to these branches of the asset pricing literature, our paper may appear also to be related to a fourth strand using alternative consumption data to improve its measurement. This literature includes Mankiw and Zeldes (1991), focusing on the consumption of stockholders and Ait-Sahalia et al. (2004) who consider a model with consumption of luxury goods. Savov (2011) uses the quantity of garbage generated as an alternative measure of consumption, and Chen and Lu (2017) who proxy time-varying consumption of durable goods by CO_2 emissions. However, the spirit of our paper is very different and focuses on whether components of the standard NIPA consumption data are substitutes. Thus, while these papers have interesting and valuable insights into asset pricing, we do not view our paper as investigating alternative measures of aggregate consumption.

2 Bundling of consumption goods

2.1 Theoretical framework

We assume that there is a representative household whose preferences can be represented by a recursive utility function V in the spirit of Epstein and Zin (1989), i.e.,

$$V_t = K(u_t, \mathcal{R}_t(V_{t+1})), \tag{1}$$

where $K : \mathbb{R}^2 \to \mathbb{R}$ is the time aggregator function and increasing in both arguments, $\mathcal{R}_t$ is a certainty equivalent function which is assumed to be homogeneous of degree one, and u_t is an intra-period utility index that quantifies the utility of the basket of consumption goods that the household consumes in period t. Assuming that K is a constant elasticity of (intertemporal) substitution aggregator and that $\mathcal{R}$ is an expected power utility certainty equivalent, we obtain the recursive utility function investigated in Epstein and Zin (1991)

$$V_t = \left[(1-\delta)\, u_t^{1-\frac{1}{\psi}} + \delta \left(\mathbb{E}_t \left[V_{t+1}^{1-\gamma} \right] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right]^{\frac{1}{1-\frac{1}{\psi}}} \tag{2}$$

where δ represents the subjective time discount rate, ψ the intertemporal elasticity of substitution, and γ denotes the coefficient of relative risk aversion.

The consumption set of the representative household comprises N different *basic consumption goods*. The quantities consumed are denoted by $C_1, \ldots, C_N$. As long as a good is not perishable, the quantity C_j is interpreted as the service flow from good j. In general, two distinct basic goods j and k in $\{1, \ldots, N\}$ may be perfect substitutes. If they are and if basic goods k and ℓ are also perfect substitutes, then goods j and ℓ are perfect substitutes as well. Hence, there are partitions, i.e., collections of subsets of $\{1, \ldots, N\}$, such that all basic consumption goods within one subset are perfect substitutes.[1] Denote these subsets by $S_1, \ldots, S_M$.

We call the collection of basic consumption goods in a subset S_i a *bundle*. Since two basic goods, whenever they are in the same bundle, are perfect substitutes, there is no need to

[1] A partition of a set Ω is a set of subsets $\Omega_1, \ldots, \Omega_M$ such that the subsets are pairwise disjoint ($\Omega_j \cap \Omega_k = \emptyset$ for $j \neq k$) and their union is Ω ($\bigcup_{j \in \{1,\ldots,M\}} \Omega_j = \Omega$).

distinguish between them from the perspective of the consumer. As a consequence, it is enough to only consider their (weighted) sum. We denote the weighted sum of consumed quantities of the basic goods within bundle i at time t by $B_{i,t}$, i.e.,

$$B_{i,t} = \sum_{j \in S_i} w_{j,t} C_{j,t}. \tag{3}$$

For two goods j and k in bundle i, the weights can be interpreted such that the consumer is indifferent between $1/w_j$ units of good j and $1/w_k$ units of good k. The weights w are necessary, since the consumed *quantities* of different types of basic consumption goods are not directly comparable.[2] Thus, in our empirical analysis, we form a Fisher index to aggregate the consumed quantities of different types of basic consumption goods to the consumed quantity for a bundle.[3]

To model the intratemporal utility index we follow Eichenbaum and Hansen (1990) and choose a constant elasticity of substitution (CES) specification, i.e., the utility index is given as

$$u_t = \left[\sum_{i=1}^{M} a_{i,t} B_{i,t}^{1-\frac{1}{\eta}} \right]^{\frac{1}{1-\frac{1}{\eta}}}, \tag{4}$$

such that $a_{i,t} > 0$ for all $i = 1, \ldots, M$ and $\sum_{i=1}^{M} a_{i,t} = 1$. Intuitively, the coefficients $a_{i,t}$ can be interpreted as the weights of the different bundles in the utility function. η is the elasticity of substitution between goods in different bundles.

The specification in Equation (3) implies that the elasticity of substitution between goods in the same bundle is infinite. As indicated by Equation (4), we assume that the substitution elasticity between *any* two pairs of bundles is the same and equal to η. Thus, on the level of basic consumption goods, any two goods are either perfect substitutes or have a substitution elasticity of η. This fact is crucial for our empirical analysis.

[2]For example, assume that the consumer considers one pineapple a perfect substitute for 20 plums. Then the number of consumed pineapples would be weighted by 1 and the number of plums by 1/20.

[3]Using a Fisher index is a standard procedure to aggregate consumed quantities of different types of consumption goods to indices (see Bureau of Economic Analysis (BEA), 2014), and boils down to adding up quantities with time-varying weights. See Appendix A for details.

This approach to aggregating goods is common in the literature. The standard consumption capital asset pricing model that assumes a single perishable good (see Lucas (1978) and Mankiw (1982, 1985)) represents a special case. Empirically, researchers typically aggregate the quantities of consumption of all non-durable goods and services (see for example Hall (1978), Mankiw and Shapiro (1986), Breeden et al. (1989), and a large number of subsequent papers that use consumption data in a single-good-framework). Durable goods are typically not included in the consumption bundle since they are not perishable. A number of papers investigate the role of consumption of the service flow of durable goods as a second bundle. Ogaki and Reinhart (1998) examines such a framework with an intratemporal utility function which is similar to the one in Equation (4) but time-additive intertemporal utility. Yogo (2006) uses the same intratemporal utility function but integrates it in a recursive intertemporal utility function that allows for non-neutral timing preferences. Lustig and Verdelhan (2007), Yang (2011), and Eraker et al. (2015) follow his approach.

A common theme of all of these papers is that non-durable goods and services represent a single bundle of consumption goods. From the perspective of the CES utility framework introduced here, these studies implicitly assume that non-durable goods and services, as well as the goods and services within these categories, are perfect substitutes. Papers that include durable goods allow durables to be complements, and assume that durable goods represent a separate bundle. In contrast, we suggest a data-driven approach for identifying bundles, which we discuss in the next section.

2.2 Testable hypotheses

In the following, for a basic consumption good j, we denote by $B_{\langle j \rangle}$ the consumed quantity of the bundle good j belongs to. Analogously, $a_{\langle j \rangle}$ denotes the weighting coefficient for the bundle in u_t.

The intratemporal marginal rate of substitution between two goods j and k is given as

$$\frac{\partial V_t/\partial C_{j,t}}{\partial V_t/\partial C_{k,t}} = \frac{\partial u_t/\partial C_{j,t}}{\partial u_t/\partial C_{k,t}} = \frac{w_{j,t}\, a_{\langle j\rangle,t} B_{\langle j\rangle,t}^{-\eta^{-1}}}{w_{k,t}\, a_{\langle k\rangle,t} B_{\langle k\rangle,t}^{-\eta^{-1}}}, \tag{5}$$

where this quantity equals w_j/w_k when consumption goods j and k are in the same bundle, i.e., when they are perfect substitutes, implying $a_{\langle j\rangle} = a_{\langle k\rangle}$ and $B_{\langle j\rangle} = B_{\langle k\rangle}$. It is well known from microeconomic theory that, given a budget constraint, the intratemporal marginal rate of substitution is equal to the relative prices consumers have to pay for consuming the two goods:

$$\frac{\partial V_t/\partial C_{j,t}}{\partial V_t/\partial C_{k,t}} = \frac{P^r_{j,t}}{P^r_{k,t}}. \tag{6}$$

Here, P^r_j denotes the rental cost of the basic consumption good for one period. If the good is consumed within that period, i.e., unless the good is durable, P^r coincides with the price of the good, which is denoted by P. In general, the rental cost of a good is equal to the price of the good today minus the discounted risk-neutral expectation of the price tomorrow after depreciation. Combining Equations (5) and (6), taking logs, and dividing by η yields

$$\kappa_{(j,k),t} + \frac{1}{\eta}\left(b_{\langle j\rangle,t} - b_{\langle k\rangle,t}\right) + p^r_{j,t} - p^r_{k,t} = 0, \tag{7}$$

where lower case letters denote logs. $\kappa_{(j,k),t}$ is a linear combination of the logs of the weights a and w of the two basic goods. This quantity is likely to only change very slowly over time, so that, locally, $\kappa_{(j,k),t}$ can be considered a constant. In our empirical analysis, we follow Yogo (2006) and assume that $\kappa_{(j,k),t} \equiv \kappa_{(j,k)}$ is constant over time.

For pairs of basic consumption goods that are perfect substitutes, i.e., for which $b_{\langle j\rangle,t} = b_{\langle k\rangle,t}$, Equation (7) implies that the rental cost of the first good must be a fixed multiple of the rental cost of the second good, so that Equation (7) simplifies to

$$\kappa_{(j,k)} + p^r_{j,t} - p^r_{k,t} = 0. \tag{8}$$

This makes sense intuitively: When the rental cost of the first good increases, consumers would rather consume the cheaper substitute. In equilibrium, rental costs must thus adjust until the initial ratio of rental costs is restored.

Our estimation approach, described below in Section 2.3, uses Equations (7) and (8) to estimate substitution elasticities and assess the likelihood of candidate partitions. However, real-world frictions might cause prices to deviate from marginal rates of substitution. For example, recent events in energy markets can lead to a situation where price shocks are not perfectly reflective of marginal utility shocks. The key question is whether demand is in fact elastic to prices. Gelman et al. (2023) estimate the price elasticity of demand for gasoline and survey the literature. They use micro-level data and find estimates between -0.20 and -0.24. This is in line with the micro-level data in their literature survey, which provides estimates ranging from -0.185 to -0.85. Aggregate data studies find similar estimates over longer time frames, but many suggest that elasticity has been decreasing in recent years. This evidence suggests that while demand for, in this case, energy may not be perfectly frictionless, it is sensitive to prices. Thus, our estimates from relative prices, while impacted by these potential frictions, should still be informative about marginal elasticities between goods.

2.3 Data and empirical approach

Consider a specific partition of the set of basic consumption goods. The chosen partition implies that for pairs of goods which are considered perfect substitutes and are thus in the same bundle, rental costs should move in lockstep as indicated by Equation (8). For the other pairs, where the two goods are in different bundles, differences in rental costs move with the differences of consumed quantities as indicated by Equation (7). This allows us to estimate η and assess the likelihood of all candidate partitions using consumption data.

We employ a GMM estimator that uses one set of moment conditions for each pair of basic consumption goods. If for the partition under consideration, the two basic goods are complements, moment restrictions corresponding to Equation (7) are used. If they are substitutes instead, we use conditions corresponding to Equation (8), which is the same as restricting η^{-1} to zero for this pair. By comparing the fit of these equations to consumption and price data across partitions, we can draw conclusions about which partition is most consistent with the data. Our exact estimation approach is detailed in Appendix B.

For the consumed quantities of the basic goods we use data from NIPA Table 2.3.3 (real personal consumption expenditures by major type of product, quantity indices) multiplied by nominal (dollar) expenditure (Table 2.3.5) in the base year (2009) and divided by population (Table 7.1). For durable goods, we transfer the annual stock of durable goods (Table 8.2 in *Fixed Assets*) to a quarterly basis as in Yogo (2006); that is we use the expenditure data in Table 2.3.3 and calculate an implied depreciation rate for each good in each year. To calculate the consumed quantity B_i of bundle i, we construct a Fisher chain-weighted index of the goods $j \in S_i$.[4] We use the NIPA price indices provided in Table 2.3.4.

In principle, rather than the prices of durable goods, we would need data on rental costs. As shown by Pakoš (2011), under mild conditions log price and log rental cost of durable goods share a common stochastic trend, with cointegrating vector $[1, -1]'$. For the cases where durable goods are involved we account for the cointegration relation using a GMM estimator that corresponds to Dynamic OLS (Stock and Watson, 1993). As described more thoroughly in Appendix B, this estimation approach includes leads and lags of the changes in the independent variable. We follow Yogo (2006) and include three leads and lags whenever durable goods are involved, but also run the estimation with more or fewer (even zero) leads and lags and find that the results are not materially dependent on the lag structure.

Our sample spans 54.5 years of quarterly data starting in 1963:Q3 and ending in 2016:Q4, where our starting date coincides with availability of returns data for asset pricing tests. Figure 1 provides an overview of the major type of products listed in the quarterly NIPA tables. Summary statistics for the growth rates of the consumption items shown in Figure 1 can be found in Table 1.

[4]Details about the data and how we construct our time series can be found in Appendix A.

2.4 Estimation results

We start with the broad categories of nondurable goods, durable goods, and services and then consider finer partitions within these categories.[5] With three basic consumption goods, there are only five ways to form bundles. Table 2 shows a ranking of these partitions by their likelihood, together with estimates of the inverse substitution elasticity, the corresponding standard errors, the log likelihood (LL) and the average root mean squared errors (RMSE) across pairs. We separate two goods by a comma if they are in the same bundle and use a backslash to indicate that goods are in distinct bundles.

We find that it is optimal to have nondurable goods (denoted by N) and services (S) in one bundle and durable goods (D) in a second one. This result is consistent across specifications, i.e., it holds in our baseline specification with three leads and lags (Panel A) as well as in the setting with zero leads and lags (Panel B). The latter specification can be motivated from theory by assuming that the rental costs of durables are proportional to their prices. In any case, the specification without leads and lags is much leaner in terms of the number of parameters to be estimated. The optimal partition again is the same with a different number of lags in the dynamic OLS approach and when using a longer sample, going back to 1947 (not reported). Comparing the RMSEs, we see that this partition is clearly better than the alternatives. The estimated inverse elasticities of 1.11 and 1.37 are clearly different from zero, implying that goods in the two separate bundles are not substitutes for one another. They correspond to elasticities of 0.9 and 0.73, similar to Yogo (2006)'s estimate of 0.79. Overall, the results in Table 2 justify the separation of durable goods from nondurables and services and, at the same time, the common practice of bundling the latter two (see Eichenbaum and Hansen, 1990; Ogaki and

[5] The top level categories in the NIPA tables are *goods* and *services*, both of which are again divided into two subcategories: *nondurable* and *durable goods* and *household consumption expenditures for services* and *consumption expenditures of nonprofit institutions serving households (NPISHs)*. While the *goods* subcategories refer to different types of goods, the *services* subcategories refer to similar services. They differ in terms of whether households directly spend money on these services or if NPISHs produce services that are not sold at market prices. Both subcategories include the same types of services, for example health care, recreation, and education. Thus, we do not consider the two subcategories of services separately. When analyzing subcategories of services, we ignore expenditures of NPISHs, since they are not subdivided into finer categories. Consumption expenditures of NPISHs make up only between 3 and 4.5% of overall services consumption expenditures.

Reinhart, 1998; Yogo, 2006; Pakoš, 2011).

We next move to more granular definitions of consumption categories. As shown in Figure 1, the NIPA tables subdivide nondurable and durable goods into four categories each and household service consumption into seven categories for a total of 15 categories. This number of categories generates 1.4 billion possible partitions, rendering a single analysis with all subcategories at one time computationally infeasible. Therefore, we start by analyzing the subcategories within the broad classes of nondurable goods, durable goods, and services and consider combinations across major categories later.

Table 3 shows the estimation results. In the category with nondurables goods (Panel A), we find that it is optimal to bundle together food (Nf) and other nondurable goods (No), but to consider clothing (Nc) and energy (Ne) as separate bundles. The estimated inverse substitution elasticity is 1.49 and there is a huge gap between the best partition and the one considering all nondurable goods as substitutes. This finding is in contrast to the common practice in the literature of using consumption of nondurables (and services) as a single basic good, i.e., treating all nondurable goods as substitutes. We also find that the best partition is much closer to the data than the partition that puts all nondurable goods in separate bundles, indicating that it is optimal to set the inverse elasticity between food and other nondurables to zero, rather than to a large positive value.

Panel B of Table 3 shows the results of a similar analysis, now using durable goods instead of nondurables. We find that it is optimal to put motor vehicles and parts (Dm), furniture (Df), and other durables (Do) in a joint bundle but to treat recreational goods and vehicles (Dr) as a second, separate bundle.

Finally, Panel C analyzes services. The best partition puts the seven types of services into four bundles. Importantly, in contrast to nondurable and durable goods, the estimate of the inverse substitution elasticity is rather small, 0.27, and the RMSE of the partition that considers all types of services as perfect substitutes of one another is very close to the RMSE of the optimal partition (0.13 vs. 0.12). For services, we find that many candidate partitions have a very similar fit to the data, all yielding inverse elasticities close to zero. Thus, we conclude that considering services as a single bundle is a reasonable assumption.

Importantly, the point estimates of η^{-1} for the best partitions are significantly different from zero, indicating that placing goods in separate bundles is statistically significantly better than putting them all together in one large bundle and, thus, considering them perfect substitutes. This is also true for goods within the services category. Still, the estimated inverse elasticity is much closer to zero for *Services* than for the two *Goods* categories. When considering all goods jointly, we again estimate a single elasticity parameter, and the estimate of 0.27 for the best partition in Panel C is closer to zero than to the estimates of 1.49 and 1.31 in Panels A and B.

We next consider nondurable goods, durable goods, and services in a joint analysis. Our estimation features six basic consumption goods: Food (Nf), Clothing and footware (Nc), Energy (Ne), Other nondurables (No), Durable goods (D), and Services (S). We also consider a version where Recreational goods and vehicles (Dr) enter the analysis as a separate good (see Table C.1 in the appendix). The optimal bundle is then identical to the one we discuss in the following but again features Recreational goods and vehicles in a separate bundle. In our later asset pricing tests, separating consumption growth of this category did not contribute to model fit (see Table F.4 in the appendix). Since separating consumption of Recreational goods and vehicles results in an increased number of parameters without improvement in fit, we do not feature this bundling in our main results.

In total, there are 203 partitions which can be formed out of six primitive consumption categories. As shown in Table 4, the partition with the highest likelihood is consistent across the two specifications.[6] It consists of three bundles: Food/Other nondurables/Services, Clothing/Durables, and Energy. This partition is reasonable from an economic point of view: For example, *Health care* and *Recreation services*, both part of *Services*, may well be substituted

[6]This is also true for specifications with one, two, and four lags in the dynamic OLS approach. Furthermore, using a longer sample, going back to 1947, and using annual rather than quarterly data results in the same partition having the highest likelihood.

by *Pharmaceutical and other medical products* and *Recreational items*, which are both part of *Other nondurable goods. Food purchased for off-premises consumption*, may be substituted by *Purchased meals and beverages* and *Food furnished to employees (including military)*, which are both part of *Services*. Consistent with the findings in Table 3, the algorithm suggests that *Clothing and footware* is not a perfect substitute for food or other nondurable goods. Indeed, the algorithm bundles clothing together with durable goods. This is in line with the argument of some authors, such as Lettau and Ludvigson (2001), who explicitly exclude *Clothing and footware* from *Nondurable goods*, because they actually appear to be durable.

Interestingly, the partition $Nf, Nc, Ne, No, S/D$, assigning *Nondurable goods* and *Services* in one bundle and separating *Durable goods* fares quite poorly and generates a substantially lower likelihood than considering *Gasoline and other energy goods* separately. Again, categorizing energy consumption as a separate bundle seems economically sensible; households cannot substitute, e.g., food for gasoline. For the best partition, η^{-1} is estimated at 1.19 in the baseline specification (1.21 in the case without leads and lags), which implies a substitution elasticity of 0.84 (0.83).

The principal conclusion that we draw from this empirical analysis is that it is highly unlikely that consumers treat energy consumption as a perfect substitute for other nondurable goods. Instead, in analyzing consumption-based models, one should treat energy as a separate bundle. In the following section, we estimate and more thoroughly analyze preference parameters in an asset pricing model where we explicitly account for the non-substitutability of energy consumption.

3 Asset pricing implications

Under the assumptions of market completeness and no arbitrage there is a unique stochastic discount factor, that is equal to the IMRS and satisfies the representative household's Euler equations,

$$E_t\left[M_{t+1}\mathbf{R}_{t+1}\right] = \mathbf{1}, \tag{9}$$

where $\mathbf{R}_{t+1}$ is a vector of gross asset returns and $\mathbf{1}$ is a vector of ones. The IMRS is given by today's price of one unit of consumption of the numeraire in state s tomorrow, i.e., it is equal to $\frac{\partial V_t/\partial B_{*,t+1,s}}{\partial V_t/\partial B_{*,t}}$. Straight-forward calculations yield

$$M_{t+1} = e^{-\delta}\left(\frac{B_{*,t+1}}{B_{*,t}}\right)^{-\frac{1}{\eta}}\left(\frac{u_{t+1}}{u_t}\right)^{\frac{1}{\eta}-\frac{1}{\psi}}\left(\frac{V_{t+1}}{\left(\mathbb{E}_t[V_{t+1}^{1-\gamma}]\right)^{\frac{1}{1-\gamma}}}\right)^{\frac{1}{\psi}-\gamma}, \tag{10}$$

where B_* denotes the consumed quantity of goods in the bundle which serves as the numeraire. Three terms impact the variation in the IMRS: The growth rate of the numeraire bundle B_*, the change in the intratemporal utility index u (see Equation (4)), reflecting changes in B_* and other goods and services, and the realized time-$t+1$ value function, relative to its certainty equivalent today. The latter term reflects changes in u and in other state variables that have an impact on the continuation value of future consumption and can be thought of as long-run risk (see Bansal and Yaron, 2004), or, more broadly, changes in the investment opportunity set (see Merton, 1973). We disentangle these effects in Appendix E.

There are three special cases of this specification of utility that we consider. The first is the standard time-additive utility case where $\gamma = 1/\psi$. In this case, the innovations in the value function no longer enter the IMRS, but different bundling of goods still potentially impacts pricing. In the second case, $\eta = \psi$, bundles are separable. Consequently, the growth rate of the utility index, u, drops out of the IMRS, and the Euler equation holds for all bundles B_1, ..., B_M, depending on the choice of the numeraire. This is the standard case considered in most applications utilizing Epstein and Zin (1989) utility, where nondurable goods and services are typically assumed to be a single bundle and are used as the numeraire.

Finally, when η goes to infinity, the growth in the numeraire drops out of the IMRS, but the growth rate of the utility index, u, remains. In this case, the utility index is just equal to the weighted sum of the consumed quantities (see Equation (4)). Economically, $\eta = \infty$ means that all goods and services are perfect substitutes for one another, so the model again boils down to a model with a single consumption good.

The opposite of this case also highlights the special role of non-substitutability: If η is small, i.e., goods are complements of one another, the growth rate of single non-substitutable goods can enter the IMRS and have a strong impact on asset prices. This can be the case even when the expenditure share on a good relative to total consumption is small. If a good is a necessity and not substitutable by other goods, then the according consumption growth rate drives the marginal utility of the investor.

The representation of the IMRS in Equation (10) is difficult to work with in empirical applications, since the value function V is not observable. Along the lines of Epstein and Zin (1991) and Yogo (2006) one can derive a formula for the return on the claim to aggregate wealth:

$$R_{w,t+1} = e^{\delta} \left(\frac{B_{*,t+1}}{B_{*,t}} \right)^{\frac{1}{\eta}} \left(\frac{u_{t+1}}{u_t} \right)^{\frac{1}{\psi} - \frac{1}{\eta}} \left(\frac{V_{t+1}}{(\mathbb{E}_t[V_{t+1}^{1-\gamma}])^{\frac{1}{1-\gamma}}} \right)^{1-\frac{1}{\psi}} \tag{11}$$

Substituting Equation (11) into Equation (10) leads to the representation

$$M_{t+1} = e^{-\delta\theta} \left(\frac{B_{*,t+1}}{B_{*,t}} \right)^{-\frac{\theta}{\eta}} \left(\frac{u_{t+1}}{u_t} \right)^{\frac{\theta}{\eta} - \frac{\theta}{\psi}} R_{w,t+1}^{\theta-1}, \tag{12}$$

where $\theta = \frac{1-\gamma}{1-\psi^{-1}}$. This representation of the IMRS will form the basis for our following empirical analyses.

3.1 Estimation Approach

We estimate the preference parameters in equations (4) and (12) via GMM. While our main focus is the three-bundle maximum likelihood partition $Nf, No, S/Nc, D/Ne$, for purposes of comparison, we also consider the partition $Nf, Nc, Ne, No, S/D$, including Nf, Nc, Ne, No, S as the separable special case, as these have been previously explored in the asset pricing literature. In our base case with three bundles, there are six parameters to estimate: the inverse IES

ψ^{-1}, the time preference rate δ, the coefficient of relative risk aversion γ, the inverse intratemporal elasticity of substitution between the different bundles η^{-1}, and the relative weighting parameters $\frac{a_2}{a_1}$ and $\frac{a_3}{a_1}$. The parameter a_1 is identified by the restriction $a_1 + a_2 + a_3 = 1$. Similarly, in the two-bundle case since $a_1 + a_2 = 1$, we estimate the ratio $\frac{a_2}{a_1}$ plus the four remaining parameters.

In practice, the parameter ψ governing the intertemporal elasticity of substitution is difficult to identify. This has led to a debate about the magnitude of the parameter in the economics literature, which largely focuses on whether it is between zero and one or greater than one. When we estimate all six parameters in an unconstrained estimation, we frequently obtain estimates of the parameter ψ that are less than zero. While this specification produces the best cross-sectional fit, it is theoretically implausible. Consequently, we restrict our consideration to models in which the IES is constrained to 1.5, to the *intra*temporal substitution parameter, and to the inverse risk aversion coefficient, respectively. Further fixed IES values and a specification where we fix the risk aversion coefficient are discussed in Appendix D.

To identify the parameters, we use two sets of moment conditions. The first set uses the intratemporal relation between prices and consumed quantities as expressed in Equation (7), where we explicitly estimate the constant given by $\log(\frac{a_k}{a_j})$. In contrast to our estimation in Section 2, we only consider a variant without any leads and lags of the logarithmic price difference. Our rationale is that the evidence in the previous section suggests that incorporating leads and lags has little impact on the estimates of η^{-1} and dramatically increases the number of moment conditions. Second, since our goal is no longer to compare the likelihoods of different partitions, we no longer consider equation (7) for each pair of consumption goods. Instead, we directly consider the three bundles (Nf, No, S), (Ne), and (Nc, D) with their corresponding relative price differences. As a result, the number of moment conditions related to identifying the parameters reduces from 30 (210 in the case with three leads and lags) to four:

$$0 = \mathbb{E}\begin{pmatrix} \log(\frac{a_2}{a_1}) + \eta^{-1}(b_{NfNoS,t} - b_{Ne,t}) + (p_{NfNoS,t} - p_{Ne,t}) \\ \left(\log(\frac{a_2}{a_1}) + \eta^{-1}(b_{NfNoS,t} - b_{Ne,t}) + (p_{NfNoS,t} - p_{Ne,t})\right)(b_{NfNoS,t} - b_{Ne,t}) \\ \log(\frac{a_3}{a_1}) + \eta^{-1}(b_{NfNoS,t} - b_{NcD,t}) + (p_{NfNoS,t} - p_{NcD,t}) \\ \left(\log(\frac{a_3}{a_1}) + \eta^{-1}(b_{NfNoS,t} - b_{NcD,t}) + (p_{NfNoS,t} - p_{NcD,t})\right)(b_{NfNoS,t} - b_{NcD,t}) \end{pmatrix}. \tag{13}$$

These conditions correspond to two OLS regressions of price differences on differences in consumed quantities, with the constraint that the two slope coefficients must be identical.

The second set of moment conditions are the Euler equations (9). An important detail in estimating parameters given this stochastic discount factor is the unobserved return on the portfolio of aggregate wealth. We approximate the return on this portfolio following Thimme and Völkert (2015) and reformulate the budget constraint $W_{t+1} = (W_t - C_t)R^w_{t+1}$ to obtain

$$R^w_{t+1} = \frac{C_{t+1}}{C_t}\frac{C_t/W_t}{C_{t+1}/W_{t+1}} \cdot \frac{1}{1 - \frac{C_t}{W_t}} \approx \frac{C_{t+1}}{C_t}\frac{\exp(cay_t - cay_{t+1})}{1 - \kappa\exp(cay_t)}.$$

Here, we approximate the consumption-to-wealth ratio by $\frac{C_t}{W_t} \approx \kappa\exp(cay_t)$, where cay is the cointegration residual of total consumption expenditures, aggregate wealth, and labor income, as introduced by Lettau and Ludvigson (2001). κ denotes the steady state consumption-to-wealth ratio. We set κ to an annual value of $1/83$, in line with the estimates of Lustig et al. (2013). However, we find that κ has only a minor impact on the parameter estimates (see Section D in the appendix).

We use a 3-month Treasury bill and 18 equity portfolios sorted on market capitalization, the book to market ratio, operating profitability, and investment as test assets. These portfolios form the basis of the factors analyzed in Fama and French (2015), and are sorted on NYSE median breakpoints for size and the 30th and 70th NYSE percentile breakpoints for the other three characteristics.[7] The use of the Treasury bill return allows us to investigate if the model

[7]These data are graciously provided by Kenneth French on his website https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

is able to address the equity premium puzzle. In total, we use 23 moment conditions to identify six parameters. Availability of the profitability portfolio return data limit the start date of our sample to the 3rd quarter of 1963. Following Campbell (1999), Yogo (2006), and Savov (2011), we use the *beginning-of-period timing convention* for consumption when we estimate the model. This means that first quarter consumption is assumed to be consumed on January 1st.

To weight the moment conditions, we use a unit weighting matrix. As discussed in Cochrane (2009), using a prespecified weighting matrix allows a direct model comparison. Using unit weights on the pricing errors implies that the parameters minimize the root mean squared pricing error, which is a statistic that is easy to interpret economically. We find that a unit weight on the first set of moment conditions, implying parameter estimates that correspond to OLS estimates, is large enough to identify η^{-1}, $\frac{a_2}{a_1}$, and $\frac{a_3}{a_1}$ through the intratemporal conditions, rather than the Euler Equations. We discuss alternative weights, focusing on asset pricing moments in Appendix D.

In the baseline approach, identification of the preference parameters can be thought of as follows: η^{-1}, $\frac{a_2}{a_1}$ and $\frac{a_3}{a_1}$ are identified by the intratemporal restriction between prices and consumed quantities. We fix ψ^{-1}, so the 19 asset pricing moments (risk free rate and 18 equity test assets) identify γ and δ. Here, δ is related to the level of the SDF and is thus pinned down by the risk-free rate. The model-implied excess return on an equity test asset is given by the negative covariance of the IMRS with the test asset return, divided by the expected value of the IMRS (see Equation (E.11) in Appendix E). The IMRS in Equation (12) can be written as

$$M_{t+1} = \left(e^{-\delta} \left(\frac{B_{*,t+1}}{B_{*,t}} \right)^{-\frac{1}{\eta}} \left(\frac{u_{t+1}}{u_t} \right)^{\frac{1}{\eta} - \frac{1}{\psi}} R_{w,t+1}^{1-\frac{1}{\theta}} \right)^{\theta}. \tag{14}$$

Given a non-zero correlation of the term in parentheses with test asset returns, the average risk premium can be matched by appropriately scaling the variance of the IMRS. From the above equation, it is clear that γ is thus identified by the average risk premium, since $\theta = \frac{1-\gamma}{1-\psi^{-1}}$.

To assess the fit of the models to the return data, we compute the model-implied risk premium (MIRP), the cross-sectional R^2, and the mean absolute pricing error (MAE). MIRP is given by the difference between the cross-sectional average of the model-implied expected returns on the equity test assets minus the model-implied risk-free rate. MIRP should be close to 1.9%, as this is the average realized risk premium per quarter in the data. The cross-sectional R^2 quantifies the relative share of the variation in expected test asset returns which can be explained by the model. MAE is given by the mean absolute difference between model-implied expected and realized average returns. We block bootstrap from the original sample and re-run the estimation on the bootstrapped sample to estimate standard errors. This procedure allows us to assess the precision of the model performance statistics and is more robust.[8]

3.2 Estimation results

In Table 5, we report parameter estimates under two specifications of consumption bundling. The first group is the bundling central to this paper; separately considering consumption of energy (which serves as the numeraire), consumption of durable goods and clothing, and consumption of the remaining nondurable goods and services.[9] The second mirrors that in Yogo (2006), and separates all nondurable goods and services consumption (serving as the numeraire here) from consumption of durable goods.

The first row of the table present point estimates for the model with three separate consumption bundles. As discussed above, the parameters η^{-1}, a_2/a_1, and a_3/a_1 are identified by moment conditions related to the relative prices of the goods. For all values of the intertemporal elasticity of substitution, the point estimates for these parameters are nearly identical; η^{-1} is close to one, and the specifications place weights of approximately 0.79, 0.02, and 0.19 on the consumption of durable goods and clothing, energy, and all other goods and services, respectively.

Point estimates of the remaining preference parameters and measures of model fit are

[8] In some specifications, the estimate of the covariance matrix of the vector of moments is numerically close to singular, which can make the usual procedure to estimate standard errors of the parameter estimates unreliable.

[9] The impact of the choice of the numeraire is discussed in Appendix B.

reasonable, with a cross-sectional R^2 of 0.51 and mean absolute pricing error of 43 basis points per quarter. Implied market risk premia are about 1.8% per quarter, or about 7% per annum. The point estimate of $\gamma = 12.37$ appears more economically reasonable and we cannot reject the hypothesis that $\gamma = 10$, a value commonly used in recent equity premium literature.

Results with the alternative bundling, presented in the second row of the table, yield similar point estimates for preference parameters. However, the cross-sectional fit deteriorates, with cross-sectional R^2 falling to 0.09, and mean absolute pricing error of approximately 60 basis points per quarter. Additionally, the model implied risk premium is only about one-quarter of that implied by the three-bundle model.[10] Thus, separating consumption into the three bundles of clothing and durables, energy, and other nondurables and services drastically improves the ability of the model to match asset pricing moments. Both the level and the cross-sectional fit of the model improve substantially when consumption is modeled using the three bundle, rather than two bundle partition.

Two special cases of the model are obtained with additional parameter restrictions. When $\psi^{-1} = \gamma$, the model reduces to the time additive case, and when $\psi^{-1} = \eta^{-1}$, preferences are intratemporally separable. The time additive case is presented in Panel B, and the intratemporally separable case in Panel C of Table 5.

The results in Panel B show that the restrictions imposed by intertemporal separability have a substantial impact on estimates of preference parameters and cross-sectional fit for both bundling schemes. In the three bundle cases, the point estimate for the coefficient of relative risk aversion is very large, $\gamma = 187.73$, although the hypothesis that the parameter is equal to zero cannot be rejected due to large standard errors. Both bundling schemes produce model implied risk premia that are essentially zero, and the cross-sectional fit deteriorates dramatically relative to the results in Table 5. These results suggest that intertemporal non-separability is extremely important for producing reasonable preference parameter estimates and matching

[10] Our point estimates are not in line with those reported in Yogo (2006) likely due to the issues raised in Borri and Ragusa (2017). They point out that, in contrast to our estimates, the parameterization in Yogo (2006) cannot explain the level of the risk-free rate.

asset pricing moments.

In contrast, setting $\eta = \psi$ has little impact on cross-sectional performance. The cross-sectional R^2 remains 0.09 for the two-bundle case and falls only slightly to 0.49 in the three-bundle case, relative to the results in Panel A. The greatest impact is seen in the estimation of preference parameters. Point estimates of ψ^{-1} in the three-bundle case continue to indicate an EIS parameter slightly greater than one and a low but imprecisely estimated coefficient of relative risk aversion $\gamma = 1.30$. The two-bundle case results in a point estimate for ψ^{-1} implying an EIS parameter less than one, and resulting negative, albeit imprecisely estimated, coefficients of rate of time preference and risk aversion.

The results indicate that, when considering implications for cross-sectional pricing, intertemporal non-separability is critical and intratemporal non-separability is less so. These implications are important in our later empirical investigations, in which we use the cross-section of average returns to estimate prices of consumption bundle risk. Intratemporal separability allows us to consider each of the individual components of consumption separately, and so motivates a specification with only energy consumption risk priced.

4 Cross-section of expected returns

4.1 A linearized factor model

In this section, we examine the implications of a linearized version of the asset pricing model in order to estimate prices of energy and other consumption bundle risks.[11] As in the previous section, we examine the performance of the model in the context of size, book-to-market, profitability, and investment portfolios. Because we are no longer imposing nonlinear restrictions on the model, we expand the original set of 18 test assets to 75, representing the intersection of size and book-to-market, operating profitability, and asset growth quintiles. Data are again

[11] The derivation of the approximate linear factor structure is described in Appendix E.

sampled at the quarterly frequency over the third quarter of 1963 through 2016.

In columns 1-4 of Table 6, we present results from estimating prices of risk from the linearized three-bundle consumption model. In columns 1 and 2, we examine the model with separate prices of risk for growth in each of the three bundles of consumption, with and without the return on the market portfolio. In columns 3 and 4, we present a model in which only energy consumption risk is priced, consistent with the restriction that the intertemporal elasticity of substitution is equal to the intratemporal elasticity of substitution.

The message across columns 1-4 is consistent: energy consumption risk exposure bears a positive and statistically significant price of risk, and neither the remaining consumption bundles nor the market return beta generates a statistically significant price of risk. Point estimates for energy consumption beta risk are consistently approximately 1.9% per quarter across the specifications, and the model explains about 45% of cross-sectional variation in average returns. The results suggest that energy consumption betas account for a sizable risk premium in the cross section and explain considerable variation in average returns.[12]

The results in columns 1-4 suggest that energy consumption risk is important, but the growth rates of the other consumption bundles and the return on the market portfolio do not add much explanatory power. The result for the market portfolio is not overly surprising given the evidence that the CAPM has difficulty in explaining variation in average asset returns and this set of asset returns in particular. The insignificance of the remaining consumption components could be due to one or more of several possible reasons.

First, measurement error may impact the market price of risk estimates for these other consumption bundles. As discussed in Savov (2011) and Kroencke (2017), precise measurement of consumption is difficult and BEA statisticians apply ample estimation and filter techniques to produce the data reported in the NIPA tables. These measurement problems apply to different

[12]Results of the same exercise for each of the 25 size- and characteristic-sorted portfolios are reported in the appendix. The results suggest similar results to these across all three sets of portfolios. The model fares best in pricing size- and operating profitability-sorted portfolios, with cross-sectional R^2 of approximately 60% and less well for size- and asset growth-sorted portfolios, with cross-sectional R^2 of approximately 40%.

degrees to different types of consumption goods and services. The discussion of the measurement procedure in the NIPA handbook suggests that energy consumption is relatively easy to measure compared to other goods and services. A second possibility is that the market prices of risk of the remaining consumption components are measured with error because they are only weakly or non-synchronously correlated with the returns on the test assets. We would expect in contrast that energy consumption shocks such as oil crises would impact both households and the broader economy at the same time.

A comparison of the point estimates from the non-linear version of the model (Table 5) with the results in Table 6 reflects this point. When estimating the non-linear model in Section 3, we forced the model to also match the level of the risk premium, i.e., the difference between equity test asset returns and the risk-free rate. It is well-known that the CAPM performs well in capturing the level of equity test asset returns - they all have positive market betas and positive average returns. Equation (E.12) in Appendix E tell us how to translate point estimates from the non-linear model into market prices of risks estimates in the linearized version of the model. Our estimates from Table 5 all correspond to a positive risk price for the market factor and a negative risk price for energy consumption growth. However, Equation (11) reveals that the return on the market also depends on consumption growth, so that several effects are mixed.

The fact that the risk price of the market factor is not identified via estimation of the linear model with these test assets implies that it is more reasonable to consider the net effects of the different consumption bundles (see Equation (E.6)). Our estimates from Table 5, with an intertemporal substitution elasticity of 1.5, combined with the factor variances, correspond to market prices of risk of 0.14% for energy consumption, 0.02% for consumption of food, other nondurables, and services, and 0.08% for consumption of durable goods. In the case of energy consumption, the estimate in the linear model is much higher, suggesting that only focusing on the cross-section of portfolio returns calls for an even lower intratemporal substitution elasticity. Holding all parameters in Table 5 fixed, except the elasticity, we need $\eta^{-1} \approx 70$ to match a market price of risk of 1.9% for energy consumption.[13]

[13]Table D.4 in Appendix D performs an estimation of the non-linear model, but puts a very low weight

In columns 5-7, we present results for alternative bundlings of consumption. Column 5 represents the standard model with nondurables and services consumption and time separable preferences, Column 6 the model with Epstein and Zin (1989) preferences, and Column 7 the model analyzed in Yogo (2006) that accounts for a price of durable consumption risk exposure. The results indicate that moving from the time separable case to including the market portfolio as in Epstein and Zin (1989) results in a positive and statistically significant price of risk for nondurable goods and services consumption exposure. However, neither the consumption of durable goods beta nor the market beta appears to bear a significant risk price.[14] Overall, the explanatory power of the model is greatly reduced relative to the energy consumption case, ranging from about 2% to 6% cross-sectional R^2.

As a point of comparison, we present results for prices of risk for factor model betas in columns 8-10. Column 8 presents results for the CAPM, in which only market beta risk is priced. Consistent with past analyses, market beta fails to generate meaningful explanatory power for the cross-section of returns. In column 9, we estimate risk prices for the Fama and French (2015) five-factor model, incorporating the market portfolio, small minus big, high minus low, conservative minus aggressive, and robust minus weak factor risk exposures as explanatory variables. In this cross-sectional context, the book-to-market (HML), investment (CMA), and profitability (RMW) exposures bear statistically significant prices of risk. The model fares quite well in terms of explanatory power, with a cross-sectional R^2 in excess of 78%.

In column 10, we add the energy consumption beta to the factor betas in estimating prices of risk. The results show that the factor risk prices are virtually unchanged, while the energy consumption beta price of risk is no longer statistically distinguishable from zero. These results suggest that some combination of the factor betas span the risk inherent in energy betas, an

on the intratemporal moment conditions. This estimation focuses on asset prices, but still forces the model to match the equity premium. We estimate an inverse intratemporal substitution elasticity of 3.45. This analysis can be considered somewhere in between the estimation of the non-linear model in Section 3 and the estimation of the linear model here.

[14]This result contrasts starkly with the results documented in Yogo (2006). In our approach, we utilize a conservative two-stage regression approach in contrast to a GMM estimator. Laurinaityte et al. (2020) discuss issues with the GMM approach in the presence of model misspecification.

issue that we will examine in more detail below. Since these factors are designed to capture risks associated with our portfolio sorting variables, it is perhaps unsurprising that they better capture cross-sectional variation in average returns.

In summary, the results suggest that energy consumption betas explain a substantial portion of the cross-sectional variation in average returns and bear a positive and significant risk price, consistent with our model. In contrast, alternative consumption bundle risk exposures generally do not seem to bear statistically significant prices of risk. These results again emphasize the importance of separation of energy consumption from the rest of the consumption bundle for understanding the relation between cross-sectional asset pricing and the consumption-based model.

4.2 Energy consumption betas

As discussed in the preceding section, risks in return-based factor models seem to subsume the risk inherent in energy consumption. In this section, we examine the betas with respect to consumption growth risk. We are interested in two issues. The first issue is that Burnside (2011) and Bryzgalova (2015) show that the empirical evidence in favor of a factor can be spurious if the factor is only weakly correlated with returns on the test assets in the time series. The second issue regards the relation between energy consumption betas and betas with respect to the Fama and French (2015) return factor exposures. As noted above, the factor risks appear to span energy consumption risk, which we examine in more detail.

Point estimates of the energy consumption growth risk exposures are shown in Panel A of Table 7. They range from 0.03 for the weak profitability and fourth quintile size portfolio to 0.85 for the small, high book-to-market portfolio. The results are generally consistent with the intuition in our cross-sectional asset pricing tests. While there are notable exceptions, there is a tendency for high book-to-market, small market capitalization, low investment, and high profitability portfolios to have higher betas than their opposite counterparts. The relationship is particularly strong across operating profitability quintiles.

We follow Delikouras and Kostakis (2019) and employ Wald tests to test several hypotheses related to the estimated betas. In particular, we estimate betas from a time-series regression using the 75 portfolio returns as dependent variables and energy consumption growth as the only factor. We test if *(i)* all betas are jointly equal to zero, *(ii)* all betas are jointly equal to the average beta, and *(iii)* the highest beta is less than or equal to the lowest beta. All three hypothesis are rejected at the 5% significance level by the Wald tests as shown in Table 8.

To more formally investigate the cross-sectional relation between energy betas and betas with respect to return factors, we perform a simple OLS regression of energy betas on the other betas and show the results in Panel B of Table 7. The table shows that energy betas are strongly positively associated with size, book-to-market, and profitability betas. However, the energy betas are not statistically significantly related to investment betas. The results suggest that energy betas capture much of the same information as size-, book-to-market, and profitability betas, and that investment betas generate a substantial amount of the additional explanatory power in Table 6.

4.3 Alternative measurement of energy consumption

Our finding that energy consumption is important to consider separately in the IMRS is consistent with evidence presented in Da et al. (2016). The authors use U.S. residential electricity consumption to measure the service flow from household capital. They find that this measure has strong explanatory power for cross-sectional variation in U.S. equity returns when used in tandem with nondurables and services consumption and the market return. While our modeling framework and interpretation are quite different, in this section we ask whether it is electricity as a component of household energy consumption that drives the results that we document above.

As a first step, we compare the time series of the electricity factor used in Da et al. (2016) with NIPA energy consumption.[15] The data used in their study are sampled at the annual

[15] We kindly thank Zhi Da for sharing these data with us.

frequency; as a result, we compare the electricity consumption data to fourth quarter over fourth quarter growth in NIPA consumption of energy. We plot the two series in Figure 2, which demonstrates a positive, but imperfect correlation of 0.29. Electricity usage is considerably more volatile than energy consumption (standard deviation of 5.98% compared to 3.33%), possibly due to differences in time aggregation. Alternatively, energy consumption may be smoother due to substitution effects between different types of energy goods and filtering performed by the Bureau of Economic Analysis (see Kroencke, 2017).

Table 9 shows estimates of market prices of risks, together with model performance statistics. We first integrate the electricity factor into our setting from Table 6, i.e., we use quarterly data and 75 portfolios, sorted by size, book-to-market ratio, investments, and profitability as test assets. Here, we use seasonally adjusted quarterly household electricity consumption growth data from the U.S. Energy Information Administration,[16] starting in 1973. Electricity usage has a large positive, but somewhat imprecisely estimated, market price of risk. The performance of the three-factor model is comparable to that of the single-factor energy consumption model. When we replace nondurables and services consumption with energy consumption in Da et al. (2016)'s framework, both the price of energy consumption and electricity usage are positive and marginally significant. This evidence suggests that there is independent information in the two series for asset returns.

Columns 4–9 uses annual data between 1956 and 2016 with December-over-December growth rates for electricity usage and Q4-over-Q4 growth rates for energy consumption. In order to compare as directly as possible to the results presented in Da et al. (2016), we use two sets of test assets: a set of 25 portfolios sorted by size and book-to-market ratio augmented by 17 industry portfolios (columns 4-6) and the set of 25 size and book-to-market sorted portfolios alone (columns 7-9). The results presented in these columns are qualitatively similar to those in columns 1-3, with the exception of the fact that the one-factor energy consumption model captures considerably less cross-sectional variation in returns than the three-factor electricity

[16] See https://www.eia.gov/electricity/monthly/.

consumption model. However, both consumption measures retain positive and marginally statistically significant prices of risk, and the results are qualitatively similar to those presented in Da et al. (2016).[17]

Our conclusion from this analysis is that while our empirical results are similar to those presented in Da et al. (2016), there is independent information in the NIPA energy consumption series from the electricity usage data. The earlier paper's focus is on quantifying the impact of the service flow from household production on asset prices, using electricity usage as a measure of this flow. Our energy consumption measure in contrast incorporates other energy goods such as gasoline and natural gas, and focuses on the limitations in finding substitutes for these goods. Our evidence suggests that both explanations may have a role to play and that although the NIPA measure of consumption in principle encompasses electricity consumption, measurement issues may obscure electricity's contribution to generating risk premia.

5 Firm-level analysis

In Section 4, we show that value and profitable stocks have high payoffs when the marginal utility of energy consumption is low and low payoffs when the marginal utility is high. A possible reason is that the production functions of value and profitable firms are on average more energy-intensive than growth and less profitable firms. As a result, their dividend streams would be particularly impacted by energy supply shocks. Formally analyzing this impact would require a production-based asset pricing model, which unfortunately is beyond the scope of this paper. We instead use this conjecture as a hypothesis to motivate an empirical examination of the dependence of these stocks on energy at the firm level.

[17] A source of difference in the results that we report for the same test assets is a different econometric approach. As mentioned above, we utilize a two-pass procedure with Shanken (1992)-corrected standard errors. Da et al. (2016) use a GMM approach similar to Yogo (2006).

5.1 Measuring energy intensity

To better understand the relation between energy consumption growth and risk premia in the cross-section of stocks, we conduct an analysis on the firm level. Our goal in this section is to define a measure for the energy intensity of a firm. We then study the properties of more or less energy-intensive firms. Energy costs are not directly visible in a firm's balance sheet. We thus use an indirect measure based on textual analysis.

We obtain the 10-K filings of all firms listed in the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system from the website of U.S. Securities and Exchange Commission (SEC). Appendix G provides details about the data source. The data set includes 10-K filings of on average 7,330 firms per year between 1993 and 2015. We apply standard procedures to clean the texts, such as erasing tables, exhibits, HTML code and stop words (see Appendix G for details). We then count the total number of words in the text and the absolute frequency of "energy words", i.e., the words *energy*, *fuel*, *gas*, and *oil*.[18]

The energy intensity of firm i, denoted by EI_i, is defined as the absolute frequency of energy words divided by the total number of words in a 10-K report. We assume that companies whose businesses heavily depend on energy goods use energy words more often in their 10-K reports than companies that are more independent of energy goods. Naturally, among those that use many energy words will be some firms from industries that are directly related to the production of energy, such as mining or refining. We will later control for the companies' industries, to check if the results also hold on the subset of firms that are likely to rather use energy goods as production inputs.

55.19% of the firm years in our sample have an energy intensity measure EI of 0, which means that none of the four energy words are mentioned in these reports. We report summary statistics for the firms with non-zero EI in Table 10. For this purpose, we pool all observations over time. We find that the measure is heavily right-skewed and leptokurtic. This is a very

[18] Alternatively, we use a more comprehensive word list that can be found in Table H.1, but the four energy words above are the most frequent (with the exception of the word *power*, which is ambiguous, as it can also be used in contexts that are not related to energy).

natural finding, given that the distribution is naturally truncated at zero.

5.2 Energy intensity and other firm characteristics

We look at the relation between our energy intensity measures and other firm characteristics. For this purpose we merge CRSP, Compustat, and the SEC databases and, as it is usual in the literature, we exclude financials and utilities from the sample. Table 11 shows the average characteristics of six portfolios. Portfolio 0 contains all stocks for which EI=0 in a particular year. The remaining stocks are sorted into quintile portfolios with respect to EI.

The key finding of the table is that firms with a low EI have on average significantly lower book-to-market ratios and lower operating profitability than firms with high EI. These results are perfectly in line with our finding in Table 7, that stocks with high energy betas also have on average high HML- and RMW-betas. The relation of EI with market betas, market capitalization, and investment is discussed more thoroughly below. Firms in portfolio 1 have a book-to-market ratio on average of 0.63. The average ratio monotonically increases to an average ratio of 0.78 in portfolio 5. The spread in book-to-market ratios is highly significant. The same is true for operating profitability which increases from 0.16 to 0.23. We use Newey and West (1987) standard errors with 24 lags to suit the fact that EI and the characteristics are very persistent.[19] In addition to looking at the difference in extreme quintile portfolios we conduct a nonparametric Wilcoxon-type test for monotonicity across ordered groups (see Cuzick, 1985) and find that it rejects the hypothesis of no trend in favor of a positive trend in 20 out of 23 years. The results are robust to the use of the alternative energy intersity measure based on the words in Table H.1.

Stocks that do not mention a single energy word have a book-to-market ratio that is on average located between the average ratios of portfolios 1 and 2, just as for operating profitability. The spreads between characteristics in portfolios 5 and 0 is slightly smaller but

[19]Robustness tests with alternative numbers of lags lead to qualitatively similar results.

have higher t-statistics, due to the fact that the average book-to-market ratio and profitability estimates of portfolio 0 are based on more observations and, thus, estimated more precisely.

We also find that market betas are decreasing in energy intensity, again in line with our findings from Panel B of Table 7. Moreover, market capitalization is higher for more energy-intensive firms. However, the spread is particularly pronounced between portfolio 0 (those without energy words in the 10-K report) and the other portfolios. This finding implies that the relation between energy intensity and the other characteristics is not a feature of small firms only. We do not find a strong relation between EI and investment in Panel A.

The latter finding changes, as soon as we exclude firms from sectors that are likely to profit from energy supply shocks (e.g., energy producers). The idea behind our analysis is that firms with a high EI use a lot of energy as a production input, an idea that may be thwarted by those firms. In Panel B, we find similar results as in Panel A, except that investments are now significantly negatively related to energy intensity. Comparing the numbers in Panels A and B indicates that it is first and foremost portfolio 5 that changes. This suggests that energy producers are often in portfolio 5 and seem to invest a lot, relative to the other firms.[20]

Our findings strongly suggest that energy-intensive firms are perceived as risky, because they are subject to the same energy-supply shocks that also affect households. Thus, these firms have low returns exactly in those periods where household energy consumption is low and marginal utility is high. This risk is reflected in higher book-to-market ratios, lower investment, and higher operating profitability. It is likely that this rationale applies in particular to industries, where there is a lot of variation in energy intensity. Table 12 shows that within firms from the *Manufacturing* sector, we see an even more pronounced relation between energy intensity and book-to-market, investment, and operating profitability, relative to the results in Table 11. In contrast, we find weaker relations when considering firms from the services sector only. Here, only about one third of the firms use at least one energy word in their reports. This is a very intuitive finding. Firms in the services sector are less likely to be dependent on energy

[20]Our finding also suggests that the weak relation between energy betas and CMA betas (see Table 7) is due to energy-producing firms.

as a primary input factor than, for example, companies in the manufacturing sector.

6 Conclusion

This paper explores the hypothesis that separating components of consumption from the standard measure of nondurables and services has implications for asset pricing. When goods are not perfect substitutes, combining them into a single consumption bundle masks the impact of these complementary goods on marginal utility. We demonstrate that within the standard set of consumption measures, the data supports separating consumption into three bundles. The first is consumption of food and beverages for off-premise consumption, other nondurable goods, and services. The second bundle comprises clothing, footwear, and durable goods. The final bundle consists of consumption of energy.

We examine the implications of this disaggregation of consumption measures for the level of and the cross-sectional variation in stock returns. First, although disaggregating consumption makes the IMRS more volatile, it is not enough to solve the equity premium puzzle in a time-additive model. Our results show that it is necessary to separate risk aversion from the inter- and intratemporal substitution elasticities to match the level of the equity premium with plausible preference parameters. Second, when it comes to explaining the cross-sectional variation in asset returns, we find that consumption-based models that bundle energy consumption with other nondurable goods and services perform poorly in explaining average returns in the cross-section of stocks. In fact, accounting for energy consumption alone provides the majority of the explanatory power for size and book-to-market-, size and investment-, and size and profitability-sorted portfolios.

Our paper dives deeper into the relation between firms' exposures to energy consumption risks and the book-to-market ratios. We use a textual analysis of firms' SEC filings to construct a measure of energy intensity. The results suggest that firms with high energy intensity tend to have high book-to-market ratios, high operating profitability, and low investment. These firms perform particularly poorly in periods of negative energy supply shocks, which hit firms and households at the same time, making them risky. This risk is driven by households' high marginal utility in low energy consumption states, as households cannot substitute other forms of consumption for energy.

One might wonder whether energy consumption risk has become less important in recent years because of the increasing independence of the U.S. economy from energy imports, often referred to as the shale revolution. It is noteworthy that this development coincides with a recent decline in the value premium in the cross-section of U.S. stocks (see, e.g., Gonçalves and Leonard, 2023; Jacobsen and Lee, 2021; Löffler, 2020). In an unreported analysis, we find that the value premium is much stronger in countries that import most of the energy goods they consume (e.g., Japan, Germany, South Korea) than in countries that are independent of energy imports (e.g., Australia, Canada). Although this pattern supports the channel we advocate, a more formal analysis would be needed to provide further insight. We defer this to future work.

It is entirely possible that the rather coarse bundles we consider mask other important variation within the consumption bundle that is relevant for asset pricing. As an example, Ait-Sahalia et al. (2004) focus on consumption of luxury goods. Aguiar and Bils (2015) examine disaggregated household consumption data to investigate whether consumption inequality has increased. They find that inequality in consumption of luxury (high elasticity) goods and services has increased despite the fact that inequality in the overall consumption bundle has not (see Krueger and Perri, 2006). Our paper suggests that consumption of goods and services that have few substitutes have implications for asset pricing.

Table 1: **Summary statistics for primitive consumption types**

	mean	std	skew	kurt	AR(1)	min	max
Nondur	0.35	0.73	0.03	1.93	0.19	-2.06	3.32
Food	0.14	0.90	0.26	2.00	0.09	-2.69	4.04
Clothing	0.67	1.43	-0.24	0.54	0.08	-4.56	4.57
Energy	0.03	1.68	-1.84	10.59	0.03	-11.82	3.75
Other	0.55	0.93	-0.63	2.37	0.30	-3.30	3.64
Durables	1.02	0.48	-0.35	-0.68	0.92	-0.11	1.98
Vehicles	0.87	1.00	0.10	-0.08	0.81	-1.72	3.58
Furnishings	0.77	0.36	0.16	-0.51	0.96	-0.01	1.55
Recr goods	1.76	0.61	0.34	0.63	0.92	0.46	3.84
Other	0.89	0.44	-0.15	-1.00	0.95	-0.12	1.82
Services	0.54	0.45	-0.27	0.12	0.56	-0.92	1.61
Housing	0.43	0.58	-0.32	-0.20	0.10	-1.33	1.69
Health care	0.65	0.83	0.76	1.93	0.53	-2.19	3.56
Transport	0.47	1.28	-0.87	1.72	0.64	-4.35	3.37
Recreation	0.77	1.31	-0.75	5.00	-0.04	-6.50	5.43
Food	0.39	1.10	0.17	0.25	0.13	-2.48	3.86
Financial	0.70	1.50	0.49	1.27	0.33	-3.65	6.44
Other	0.42	0.97	-0.16	0.76	0.35	-3.03	3.61

Summary statistics. The time series are quarterly log growth rates of the respective consumption index for the period from 1963:Q3 to 2016:Q4, expressed in percentage points. The data are constructed as described in Appendix A. *kurt* denotes excess kurtosis.

Table 2: **Parameter estimates, likelihood, and average RMSE**

rnk(LL)	Partition	$\widehat{\eta^{-1}}$	se	LL	RMSE
Panel A: Three leads and lags					
1	$N, S/D$	1.11	(0.05)	270.11	0.18
2	$N/D/S$	1.16	(0.16)	−107.12	0.30
3	$N, D/S$	2.25	(0.40)	−162.05	0.33
4	N, D, S	–	–	−276.54	0.38
5	$N/D, S$	0.54	(0.16)	−307.11	0.40
Panel B: No leads and lags					
1	$N, S/D$	1.37	(0.04)	464.56	0.12
2	$N/D/S$	1.25	(0.04)	61.61	0.23
3	$N, D/S$	3.09	(0.13)	0.48	0.27
4	N, D, S	–	–	−163.80	0.34
5	$N/D, S$	0.96	(0.14)	−180.29	0.36

Results of estimation as outlined in Section 2. The primitive consumption categories are *nondurable goods* (N), *durable goods* (D), and *services* (S). Primitive consumption categories belonging to the same bundle are separated by commas, and the different bundles are separated by slashes. se denotes the standard error of $\widehat{\eta^{-1}}$, LL is the log likelihood, and RMSE is the average root mean squared error, i.e., the average of $\widehat{\sigma}_{(j,k)}$ as defined in Appendix B. Panel A shows results of the baseline specification with three leads and lags, while panel B shows results of the alternative specification without any leads and lags. All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

Table 3: **Parameter estimates, likelihood, and average RMSE**

rnk(LL)	Partition	$\widehat{\eta^{-1}}$	se	LL	RMSE
Panel A: Nondurable goods, no leads and lags					
1	$Nf, No/Nc/Ne$	1.49	(0.06)	638.39	0.16
2	$Nf, Ne, No/Nc$	1.81	(0.13)	241.06	0.22
3	$Nf/Nc/Ne/No$	1.41	(0.06)	−114.80	0.28
4	$Nf, Nc, No/Ne$	2.26	(0.11)	−157.99	0.33
5	$Nf/Nc, No/Ne$	1.54	(0.06)	−178.98	0.33
6	Nf, Nc, Ne, No	–	–	−268.39	0.36
Panel B: Durable goods, three leads and lags					
1	$Dm, Df, Do/Dr$	1.31	(0.04)	284.24	0.21
2	$Dm/Df, Do/Dr$	0.98	(0.14)	−29.74	0.27
3	$Dm, Do/Df/Dr$	0.94	(0.13)	−45.76	0.28
4	$Dm, Df/Do/Dr$	0.93	(0.14)	−68.64	0.28
5	$Dm/Df/Dr/Do$	0.93	(0.14)	−82.44	0.28
7	Dm, Df, Dr, Do	–	–	−477.58	0.41
Panel C: Services, no leads and lags					
1	$Su/Sh, St, Sr/Sf, So/Si$	0.27	(0.07)	4595.88	0.12
2	$Su, Sf, So/Sh, St, Sr/Si$	0.27	(0.07)	4547.59	0.12
3	$Su, So/Sh, St, Sr/Sf/Si$	0.24	(0.07)	4505.17	0.12
4	$Su/Sh, St, Sr/Sf/Si/So$	0.25	(0.07)	4493.16	0.12
5	$Su, Sf/Sh, St, Sr/Si/So$	0.29	(0.07)	4486.96	0.12
52	$Su, Sh, St, Sr, Sf, Si, So$	–	–	3781.61	0.13
368	$Su/Sh/St/Sr/Sf/Si/So$	0.80	(0.03)	2481.84	0.16

Results of estimation as outlined in Section 2. The primitive consumption categories in Panel A are *Food and beverages purchased for off-premises consumption* (Nf), *Clothing and footwear* (Nc), *Gasoline and other energy goods* (Ne), and *Other nondurable goods* (No). In Panel B, they are *Motor vehicles and parts* (Dm), *Furnishings and durable household equipment* (Df), *Recreational goods and vehicles* (Dr), and *Other durable goods* (Do). In Panel C, the categories are *Housing and utilities* (Su), *Health care* (Sh), *Transportation services* (St), *Recreation services* (Sr), *Food services and accommodations* (Sf), *Financial services and insurance* (Si), and *Other services* (So). Primitive consumption categories belonging to the same bundle are separated by commas, and the different bundles are separated by slashes. se denotes the standard error of $\widehat{\eta^{-1}}$, LL is the log likelihood, and RMSE is the average root mean squared error, i.e., the average of $\widehat{\sigma}_{(j,k)}$ as defined in Appendix B. There are 15 (877) possible partitions, i.e., ways to bundle these four (seven) goods. The table only shows the five partitions with the highest likelihood and the partitions placing all goods in separate bundles/in one bundle. All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

Table 4: **Parameter estimates, likelihood, and average RMSE**

rnk(LL)	Partition	$\widehat{\eta^{-1}}$	se	LL	RMSE
Panel A: Three leads and lags					
1	$Nf, No, S/Nc, D/Ne$	1.19	(0.06)	326.43	0.24
2	$Nf, S/Nc, D/Ne/No$	1.20	(0.06)	174.54	0.25
3	$Nf, No, S/Nc/Ne/D$	1.42	(0.10)	−174.83	0.30
4	$Nf, No/Nc, D/Ne/S$	1.18	(0.05)	−294.42	0.28
5	$Nf, S/Nc/Ne/No/D$	1.41	(0.10)	−321.84	0.31
31	$Nf/Nc/Ne/No/S/D$	1.23	(0.06)	−1084.39	0.36
87	$Nf, Nc, Ne, No, S/D$	1.82	(0.12)	−1598.27	0.51
153	Nf, Nc, Ne, No, S, D	–	–	−2025.19	0.61
Panel B: No leads and lags					
1	$Nf, No, S/Nc, D/Ne$	1.21	(0.04)	1851.68	0.16
2	$Nf, Ne, No, S/Nc, D$	1.66	(0.05)	1589.71	0.16
3	$Nf, S/Nc, D/Ne/No$	1.21	(0.04)	1560.08	0.17
4	$Nf, Ne, S/Nc, D/No$	1.71	(0.06)	1380.68	0.17
5	$Nf, S/Nc, D/Ne, No$	1.56	(0.06)	1367.33	0.18
29	$Nf, Nc, Ne, No, S/D$	1.62	(0.06)	197.83	0.29
45	$Nf/Nc/Ne/No/S/D$	1.23	(0.05)	−95.06	0.27
97	Nf, Nc, Ne, No, S, D	–	–	−509.19	0.35

Results of estimation as outlined in Section 2. The primitive consumption categories are *food and beverages purchased for off-premises consumption* (Nf), *clothing and footwear* (Nc), *gasoline and other energy goods* (Ne), *other nondurable goods* (No), *services* (S), and *durable goods* (D). Primitive consumption categories belonging to the same bundle are separated by commas, and the different bundles are separated by slashes. se denotes the standard error of $\widehat{\eta^{-1}}$, LL is the log likelihood, and RMSE is the average root mean squared error, i.e., the average of $\widehat{\sigma}_{(j,k)}$ as defined in Section 2.3. There are 203 possible ways to bundle these six goods. The table only shows the five partitions with the highest likelihood, the partition that separates durable goods from all other goods, and the partitions placing all goods in separate bundles/in one bundle. Panel A shows results of the baseline specification with three leads and lags, while panel B shows results of the alternative specification without any leads and lags. All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

Table 5: **Estimating preference parameters**

Partition	ψ^{-1}	δ	γ	η^{-1}	a_2/a_1	a_3/a_1	MIRP	R^2	MAE
Panel A: IES constrained to 1.5									
$Nf, No, S/Nc, D/Ne$	2/3	0.0069	12.37	0.99	0.13	4.28	0.0181	0.51	0.0043
		(0.0016)	(4.90)	(0.16)	(0.05)	(0.73)	(0.0060)	(0.18)	(0.0012)
$Nf, Nc, Ne, No, S/D$	2/3	0.0086	11.20	1.58	9.54		0.0049	0.09	0.0061
		(0.0381)	(14.63)	(0.43)	(4.58)		(0.0051)	(0.12)	(0.0011)
Panel B: Time-additive model ($\gamma = \psi^{-1}$)									
$Nf, No, S/Nc, D/Ne$	187.73	−1.2229	187.73	0.98	0.13	4.36	0.0001	0.20	0.0050
	(102.94)	(0.06913)	(102.94)	(0.16)	(0.05)	(0.74)	(0.0047)	(0.17)	(0.0012)
$Nf, Nc, Ne, No, S/D$	10.03	−0.0668	10.03	1.62	9.09		−0.0001	0.01	0.0059
	(7.42)	(0.0636)	(7.42)	(0.43)	(4.58)		(0.0003)	(0.02)	(0.0013)
Panel C: Intratemporally separable model ($\eta = \psi$)									
$Nf, No, S/Nc, D/Ne$	0.99	0.0041	1.30	0.99	0.13	4.32	0.0177	0.49	0.0045
	(0.16)	(0.0381)	(4.86)	(0.16)	(0.06)	(0.86)	(0.0073)	(0.20)	(0.0013)
$Nf, Nc, Ne, No, S/D$	1.58	−0.0001	−16.51	1.58	9.51		0.0057	0.09	0.0062
	(0.43)	(0.0385)	(15.29)	(0.43)	(4.58)		(0.0058)	(0.10)	(0.0012)

Point estimates of the preference parameters with bootstrapped standard errors in parentheses. In Panel A, the inverse IES ψ^{-1} is fixed to 2/3. In Panel B, the inverse IES ψ^{-1} is constrained to be equal to the coefficient of relative risk aversion γ. In Panel C, the intertemporal and intratemporal substitution elasticities are constrained to be equal, i.e., $\psi = \eta$. We also report the model-implied risk premium (MIRP), the cross-sectional R^2 and the mean absolute pricing error (MAE) for the returns on a 3-month Treasury Bill and a set of 18 portfolios sorted on size, book-to-market ratio, asset growth, and operating profitability. The primitive consumption categories are *food and beverages purchased for off-premises consumption* (Nf), *clothing and footwear* (Nc), *gasoline and other energy goods* (Ne), *other nondurable goods* (No), *services* (S), and *durable goods* (D). Primitive consumption categories belonging to the same bundle are separated by commas, and the different bundles are separated by slashes. All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

Table 6: **Market prices of risks**

	Our model				Other consumption models			CAPM	Fama/French	
	1	2	3	4	5	6	7	8	9	10
Ne	1.91**	1.93***	1.89**	1.91**						0.37
	[2.02]	[2.66]	[2.16]	[2.33]						[1.04]
Nf, No, S	0.10	0.12								
	[0.34]	[1.07]								
Nc, D	-0.05	-0.05								
	[−0.27]	[−0.28]								
Nf, Nc, Ne, No, S					0.11	0.28***	0.27***			
					[0.55]	[2.73]	[2.69]			
D							0.28			
							[1.47]			
MKT		0.27		0.36		0.54	0.45	0.18	0.69	1.02
		[0.19]		[0.25]		[0.45]	[0.38]	[0.17]	[0.66]	[1.08]
SMB									0.62	0.61
									[1.57]	[1.56]
HML									0.98**	0.96**
									[2.46]	[2.39]
CMA									0.79***	0.78***
									[2.77]	[2.73]
RMW									0.58*	0.60**
									[1.91]	[1.97]
const	1.73*	1.75	1.51	1.67	1.69**	1.82*	1.85*	2.10***	1.01	0.70
	[1.65]	[1.30]	[1.57]	[1.29]	[2.20]	[1.85]	[1.86]	[2.58]	[1.23]	[0.96]
MAE	0.36	0.36	0.35	0.35	0.50	0.49	0.49	0.51	0.22	0.21
R^2	45.81	45.84	44.96	45.14	2.28	4.58	6.25	0.27	78.27	78.69

Market prices of risk estimates in a linear factor model. An intercept is included in the cross-sectional regression. We use 75 test assets, consisting of 25 portfolios sorted by size and book-to-market ratio, 25 sorted by size and investment, and 25 sorted by size and profitability. We use portfolio returns in excess of the cumulative 3-month Treasury bill rate. Mean absolute errors (MAE) and R^2s are expressed in percentage points. The primitive consumption categories are *food and beverages purchased for off-premises consumption* (Nf), *clothing and footwear* (Nc), *gasoline and other energy goods* (Ne), *other nondurable goods* (No), *services* (S), and *durable goods* (D). All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

Table 7: **Betas**

Panel A: Energy betas of test assets

	Small	2	3	4	Big
Low	0.41	0.26	0.27	0.10	0.53
2	0.40	0.53	0.23	0.30	0.28
3	0.67	0.60	0.57	0.30	0.09
4	0.67	0.69	0.35	0.38	0.33
High	0.85	0.83	0.50	0.30	0.30
Conservative	0.55	0.41	0.57	0.29	0.05
2	0.71	0.56	0.44	0.23	0.13
3	0.78	0.75	0.35	0.30	0.36
4	0.62	0.81	0.40	0.31	0.49
Aggressive	0.51	0.31	0.14	0.08	0.26
Weak	0.39	0.35	0.27	0.03	0.08
2	0.80	0.53	0.22	0.07	0.24
3	0.69	0.63	0.21	0.28	0.27
4	0.83	0.54	0.44	0.24	0.29
Robust	0.69	0.52	0.46	0.45	0.48

Panel B: Relation between energy betas and factor betas

const	β_{MKT}	β_{SMB}	β_{HML}	β_{CMA}	β_{RMW}	R^2
1.02***	-0.79***	0.22***	0.24***	-0.00	0.19***	0.65
[3.55]	[-2.79]	[6.91]	[3.73]	[-0.06]	[3.62]	
	0.21***	0.24***	0.26***	0.03	0.23***	0.58
	[8.14]	[7.24]	[3.76]	[0.41]	[4.07]	

Panel A shows energy betas which are estimated via time series regressions of portfolio returns on log growth in energy consumption. Panel B shows results from a cross-sectional regression of energy betas (shown in Panel A) on market-, SMB-, HML-, CMA-, and RMW-betas. All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

Table 8: **Identification tests for energy betas**

	Hypothesis		
	$\hat{\beta}_i = 0 \ \ \forall i$	$\hat{\beta}_i = \hat{\beta}_j \ \ \forall i, j$	$\hat{\beta}_{\max} = \hat{\beta}_{\min}$
Wald	181.868	179.976	6.229
p-val	0.000	0.000	0.013

Wald tests that test the hypotheses if all betas are equal to zero, if all betas are equal to one another, and if the largest beta is equal to the smallest beta. Betas are full sample betas that are estimated via time series regressions of portfolio returns on log growth in energy consumption. Test assets are 25 portfolios sorted by size and book-to-market ratio, 25 sorted by size and investment, and 25 sorted by size and profitability. We use portfolio returns in excess of the cumulative 3-month Treasury bill rate. All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

Table 9: **Market prices of risks with electricity factor**

	Quarterly data			Annual data					
	75 size/value/inv/prof			25 size/value + 17 ind			25 size/value		
	1	2	3	4	5	6	7	8	9
Ne	1.68**		1.47*	1.95**		2.36*	3.48**		2.58*
	[2.11]		[1.83]	[1.96]		[1.93]	[2.16]		[1.78]
Nf, Nc, Ne, No, S		0.12			1.30**			1.53**	
		[0.78]			[2.09]			[2.10]	
MKT		-1.03	-0.50		2.32	2.73		2.90	2.56
		[−0.57]	[−0.31]		[0.43]	[0.51]		[0.43]	[0.40]
electricity		5.63*	3.62*		3.16	5.02**		4.75	6.90*
		[1.67]	[1.82]		[1.32]	[1.98]		[1.60]	[1.93]
const	1.57	3.22*	2.65*	6.80**	5.91	5.51	5.44	5.16	5.58
	[1.52]	[1.87]	[1.78]	[2.50]	[1.27]	[1.19]	[1.28]	[0.84]	[0.96]
MAE	0.35	0.36	0.32	1.90	1.35	1.47	1.76	1.01	1.24
R^2	47.19	43.69	56.91	20.55	47.57	43.33	33.59	69.66	61.43

Market prices of risk estimates in a linear factor model. An intercept is included in the cross-sectional regression. In columns 1, 2, and 3 test assets are 25 portfolios sorted by size and book-to-market ratio, 25 sorted by size and investment, and 25 sorted by size and profitability. We use quarterly data between 1973:Q2 and 2016:Q4. In columns 4, 5, and 6 test assets are 25 portfolios sorted by size and book-to-market ratio and 17 portfolios sorted by industry. The data are annual between 1956 and 2016 and we use fourth quarter over fourth quarter growth rates for NIPA consumption measures and December over December growth rates for electricity consumption. In columns 7, 8, and 9 test assets are 25 portfolios sorted by size and book-to-market ratio only. As in columns 4, 5, and 6, the data are annual between 1956 and 2016 and growth rates are fourth quarter over fourth quarter/December over December. All portfolio returns are in excess of the cumulative 3-month Treasury bill rate over the respective horizons. Root mean squared errors (RMSE) and R^2s are expressed in percentage points. The primitive consumption categories are *food and beverages purchased for off-premises consumption* (Nf), *clothing and footwear* (Nc), *gasoline and other energy goods* (Ne), *other nondurable goods* (No), *services* (S), and *durable goods* (D). Details on the data are provided in Appendix A.

Table 10: **Summary statistics for energy intensity measure**

Panel A: Moments								
mean	std	var	skew	kurt	min	max		
0.5263	1.0920	1.1924	3.0346	13.6706	<0.0001	10.4265		
Panel B: Percentiles								
1%	5%	10%	25%	50%	75%	90%	95%	99%
0.0023	0.0043	0.0064	0.0146	0.0536	0.3767	1.8606	3.0986	5.1010

Summary statistics of the energy intensity measure EI expressed in percentage points. Details about the construction of EI are provided in Appendix G. The results are based on annual data from 1993 till 2015.

Table 11: **Characteristics of EI-sorted portfolios**

	0	1	2	3	4	5	5-0	t	5-1	t
Panel A: All firms										
mkt beta	1.03	1.13	1.08	1.05	1.02	0.92	-0.12	[-2.02]	-0.21	[-3.75]
mkt cap	5.62	5.92	5.77	5.94	6.05	6.20	0.57	[8.98]	0.28	[4.03]
book/mkt	0.66	0.63	0.67	0.71	0.75	0.78	0.12	[10.19]	0.15	[9.79]
inv	0.14	0.16	0.12	0.12	0.11	0.15	0.01	[0.53]	-0.01	[-0.45]
op prof	0.17	0.16	0.19	0.24	0.24	0.23	0.06	[4.25]	0.07	[4.06]
Panel B: Exclude energy-related industries										
mkt beta	1.15	1.20	1.14	1.09	1.04	1.08	-0.06	[-1.52]	-0.12	[-2.85]
mkt cap	5.61	5.92	5.74	5.90	5.97	6.07	0.46	[7.12]	0.15	[2.38]
book/mkt	0.69	0.66	0.68	0.71	0.75	0.76	0.06	[2.47]	0.10	[3.47]
inv	0.14	0.15	0.12	0.12	0.11	0.12	-0.02	[-2.34]	0.03	[-2.44]
op prof	0.18	0.17	0.20	0.23	0.24	0.22	0.04	[5.15]	0.05	[4.91]

Characteristics of portfolios sorted with respect to EI. Portfolio 0 consists of stocks for which EI = 0. The market capitalization is expressed in logarithms of millions of dollars. Details about the construction of the characteristics and the data are provided in Appendix A. Panel A shows average characteristics of firms using all firms in our sample. Panel B shows average characteristics of firms that are not in one of following sectors: Mining, except metal mining (SIC codes between 1200 and 1500), Chemicals and Allied Products + Petroleum Refining and Related Industries (SIC codes between 2800 and 3000), Electric, Gas and Sanitary Services (SIC codes between 4900 and 5000), or Gasoline Service Stations (SIC codes between 5540 and 5550).

Table 12: **Industry-specific relations between EI and characteristics**

	0	1	2	3	4	5	5-0	t	5-1	t
Panel A: Manufacturing sector only										
mkt beta	1.16	1.21	1.13	1.09	1.04	1.11	-0.05	[-1.02]	-0.11	[-1.92]
log mkt cap	5.57	5.83	5.79	6.04	6.10	6.39	0.82	[11.28]	0.56	[6.78]
book/mkt	0.61	0.58	0.63	0.69	0.72	0.72	0.12	[5.22]	0.14	[4.17]
inv	0.13	0.15	0.10	0.11	0.10	0.11	-0.03	[-3.67]	-0.04	[-3.97]
op prof	0.14	0.15	0.19	0.23	0.24	0.23	0.08	[5.44]	0.08	[5.52]
Panel B: Services sector only										
mkt beta	1.20	1.31	1.24	1.16	1.18	1.00	-0.20	[-4.07]	-0.31	[-5.01]
log mkt cap	5.66	6.19	5.86	5.61	5.51	5.56	-0.10	[-1.84]	0.64	[-8.64]
book/mkt	0.61	0.55	0.52	0.68	0.66	0.67	0.06	[1.49]	0.12	[2.86]
inv	0.17	0.18	0.18	0.15	0.14	0.16	-0.01	[-1.20]	-0.03	[-1.72]
op prof	0.18	0.18	0.16	0.20	0.20	0.22	0.04	[3.27]	0.04	[1.81]

Characteristics of portfolios sorted with respect to EI. Portfolio 0 consists of stocks for which EI = 0. The market capitalization is expressed in logarithms of millions of dollars. Details about the construction of the characteristic and the data are provided in Appendix A. Panel A shows average characteristics of firms in the manufacturing section (SIC codes between 2000 and 4000). Panel B shows average characteristics of firms in the services sector (SIC codes between 7000 and 9000).

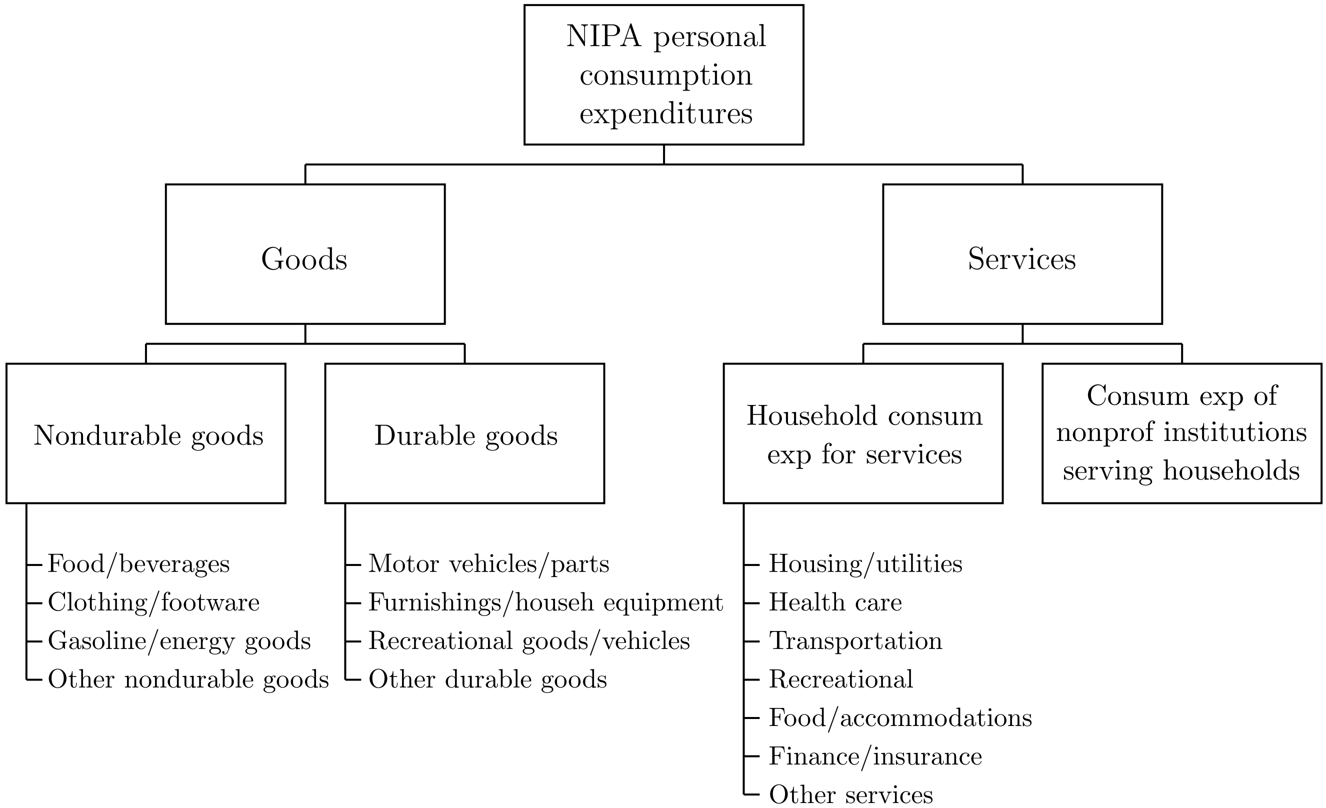

Figure 1: Overview of consumption categories as classified by the Bureau of Economic Analysis in their National Income and Product Accounts tables.

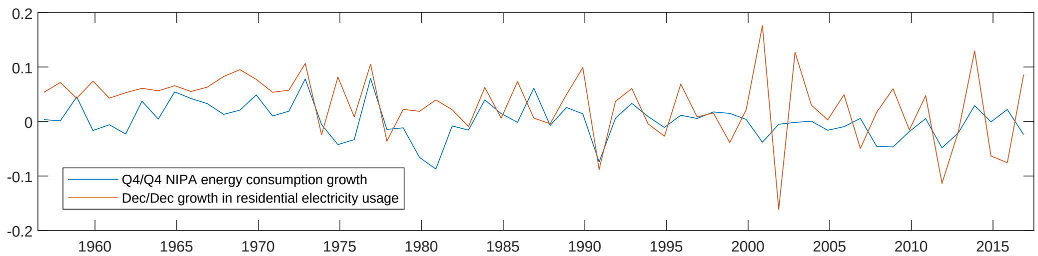

Figure 2: Comparison of fourth quarter-over-fourth quarter NIPA energy consumption growth with December-over-December growth in residential electricity usage. The former time series is constructed as described in Appendix A. The latter was kindly provided by Zhi Da and its construction is described in Da et al. (2016).

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A Data

Consumption data. We exclusively use macroeconomic data provided by the Bureau of Economic Analysis at the U.S. Department of Commerce. The data can be retrieved from the *GDP & Personal Income* section at https://www.bea.gov/iTable/index_nipa.cfm. For all goods that are categorized as nondurable and for services, we use consumption data from Table 2.3.3 (real personal consumption expenditures by major type of product, quantity indexes). We multiply the quantity index for each type of product by the nominal (dollar) expenditure (Table 2.3.5) of the respective good in the base year. Finally, we divide all quantities by U.S. population which is provided in Table 7.1.

For durable goods, we use the annual stock of durable goods (Table 8.2 in *Fixed Assets*) and, just as explained above, multiply by dollar expenditure in the base year and divide by population. Since we work with quarterly data, we follow Yogo (2006) in constructing quarterly time series. This means that we calculate an implicit depreciation rate for each good in each year such that the stock at the end of year t plus the quarterly expenditures from Table 2.3.3 minus depreciation equals the stock at the end of year $t+1$. We assume that depreciation rates are constant within years for each good which yields the stock for each quarter.

In Equation (3) in Section 2.1, we use the notation $B_{i,t} = \sum_{j=1}^{N} C_{j,t} \mathbb{1}_{j \in S_i}$ for bundles of goods. In the data, we combine consumption goods to bundles by forming Fisher chain-weighted quantity indexes of the consumption goods $j \in S_i$ for each bundle i. In particular, we calculate

$$B_{i,t} = \sqrt{\frac{\sum_{j \in S_i} P_{j,t-1} C_{j,t}}{\sum_{j \in S_i} P_{j,t-1} C_{j,t-1}} \times \frac{\sum_{j \in S_i} P_{j,t} C_{j,t}}{\sum_{j \in S_i} P_{j,t} C_{j,t-1}}}\, B_{i,t-1}.$$

The BEA uses the same procedure to form indexes (such as "nondurable goods" from the different types of nondurables or "goods" from nondurable and durable goods). This allows a simple plausibility check of our procedure.

Asset pricing factors. We use factors, more precisely the return on the value-weighted CRSP stock market index, SMB, HML, CMA, and RMW portfolio returns, from Kenneth French's data library mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Test asset returns. All returns on risky test assets that are used in the asset pricing tests in Section 3 are portfolio returns that were downloaded from Kenneth French's homepage. 3-month Treasury bill rates are from the Board of Governors of the Federal Reserve System (see https://www.federalreserve.gov/datadownload/Choose.aspx?rel=H15).

Data on individual stocks. We merge CRSP, Compustat and the database that is publicly available on the website of the U.S. Securities and Exchange Commission (SEC) via https://www.sec.gov. Details how we process the SEC data are provided in Appendix G. We use data on stock prices, market capitalization, and stock returns from CRSP. In particular, we use all actively traded common stocks that are traded at the NYSE, AMEX, or NASDAQ. We follow Shumway (1997) to account for delisting returns. We estimate market betas for individual stocks from rolling window regressions. The windows are 60 months in which at least 24 return observations must be available. All other firm characteristics are constructed from Compustat data. We calculate book-to-market ratios as in Davis et al. (2000) and profitability and investment as in Fama and French (2016).

B Details about the GMM estimation in Section 2

We first discuss our estimation approach under the assumption that rental costs of durable goods are proportional to the price of durable goods. The second part of this section deals with the situation when they are only cointegrated. For a specific partition, the proportionality assumption, together with Equation (7) implies the restriction

$$b_{\langle k\rangle,t} - b_{\langle j\rangle,t} = \eta\kappa_{(j,k)} + \eta(p_{j,t} - p_{k,t}) + \zeta_{(j,k),t}, \tag{B.1}$$

where for basic goods j and k in the same bundle, the left-hand side would be equal to zero. Based on Equation (B.1), one could perform a linear regression of the difference in consumed quantities on the price difference to estimate the substitution elasticity between goods j and k. Our empirical approach deviates from this regression-based approach in two ways.

First, instead of estimating one substitution elasticity for each pair of basic consumption goods, we estimate a single coefficient η, which represents the substitution elasticity between basic goods for pairs of goods in separate bundles. Remember that the CES specification of the utility index in Equation (4) implies that the elasticity is equal to a single value η for basic goods in separate bundles. To do so, we use a GMM approach estimating one single parameter η but separate intercept terms $\kappa_{(j,k)}$ for each pair of basic consumption goods (j,k) with $j < k$.

Second, instead of directly using Equations (B.1) for the different pairs of basic goods as moment conditions (i.e., $\mathbb{E}_T[\zeta_{(j,k),t}] = 0$ and $\mathbb{E}_T[\zeta_{(j,k),t}(p_{j,t} - p_{k,t})] = 0$ for all pairs (j,k) with $j < k$, where we use the notation $\mathbb{E}_T[X_t] = \frac{1}{T}\sum_{t=1}^{T} X_t$), we divide Equation (B.1) by η. We define

$$\varepsilon_{(j,k),t} = \frac{\zeta_{(j,k),t}}{\eta} = p_{k,t} - p_{j,t} + \frac{1}{\eta}(b_{\langle k\rangle,t} - b_{\langle j\rangle,t}) - \kappa_{(j,k)}. \tag{B.2}$$

Our GMM estimator is then based on the sample moment conditions

$$g_T\begin{pmatrix} \eta^{-1} \\ \kappa_{(1,2)} \\ \kappa_{(1,3)} \\ \dots \\ \kappa_{(N-1,N)} \end{pmatrix} = \mathbb{E}_T\begin{bmatrix} \varepsilon_{(1,2),t} \\ \varepsilon_{(1,2),t}(p_{1,t} - p_{2,t}) \\ \varepsilon_{(1,3),t} \\ \varepsilon_{(1,3),t}(p_{1,t} - p_{3,t}) \\ \dots \\ \varepsilon_{(N-1,N),t} \\ \varepsilon_{(N-1,N),t}(p_{N-1,t} - p_{N,t}) \end{bmatrix}. \tag{B.3}$$

For pairs (j,k) where the basic goods j and k are in different bundles, setting the two moment conditions $\mathbb{E}_T[\varepsilon_{(j,k),t}]$ and $\mathbb{E}_T[\varepsilon_{(j,k),t}(p_{j,t} - p_{k,t})]$ to zero yields a consistent estimate of η^{-1}, where η is the slope coefficient in the linear relation in Equation (B.1). Estimating η^{-1} allows a simple test of the null $\eta^{-1} = 0$, which would imply that goods in different bundles are also perfect substitutes.

For a pair (j,k) where the basic goods j and k are in the same bundle, η^{-1} drops out of the respective moment condition, since $b_{\langle k\rangle,t} = b_{\langle j\rangle,t}$. Put differently, η^{-1} can only be identified from pairs where the two basic goods are in different bundles. With basic goods j and k in the same bundle, $\varepsilon_{(j,k),t} = p_{k,t} - p_{j,t} - \kappa_{(j,k)}$, so that the moment conditions imply that the variance of the log price difference is equal to zero, i.e., prices move in lockstep.[21]

The GMM estimator based on Equation (B.3) uses $2 \cdot \binom{N}{2}$ moment conditions to estimate $\binom{N}{2}+1$ parameters. Note that the number of moment conditions and the number of parameters to be estimated are the same for all candidate partitions. The partitions only differ with respect to for which pairs (j,k) the right-hand side of Equation (B.2) contains a term involving the consumed quantities $b_{\langle j\rangle,t}$ and $b_{\langle k\rangle,t}$. We use a unit matrix to weight the moment conditions.

To evaluate the goodness of fit of a candidate partition, we calculate the likelihood assuming that the error terms $\varepsilon_{(j,k),t}$ are i.i.d. Gaussian with a zero mean as implied by the model. In particular, we estimate the standard deviation $\sigma_{(j,k)}$ of $\varepsilon_{(j,k),t}$ by $\widehat{\sigma}_{(j,k)} = \sqrt{\frac{1}{T}\sum_t \varepsilon^2_{(j,k),t}}$. The log likelihood (LL) is then given by

$$\mathrm{LL} = \sum_{j<k} \left(-\frac{T}{2} \log(2\pi\, \widehat{\sigma}^2_{(j,k)}) - \frac{\sum_t \varepsilon^2_{(j,k),t}}{2\widehat{\sigma}^2_{(j,k)}} \right) = \sum_{j<k} \left(-\frac{T}{2} \left(\log(\widehat{\sigma}^2_{(j,k)}) + 1 + \log(2\pi) \right) \right). \tag{B.4}$$

We perform the estimation and the computation of the (log) likelihood for all possible partitions of the set $\{1,\ldots,N\}$, yielding a ranking of the partitions with respect to their fit to the data.

We now describe the estimator under the assumption that log price and log rental cost of durable goods share a common stochastic trend, with cointegrating vector $[1,-1]'$, which holds under mild conditions (see Pakoš, 2011, Proposition 3). Given our utility index, this implies a cointegration relation between $b_{\langle j\rangle} - b_{\langle k\rangle}$ and $p_j - p_k$ with cointegrating vector $[1,\eta]'$. We follow Lettau and Ludvigson (2001) and Yogo (2006) and estimate the vector with Dynamic OLS as established by Stock and Watson (1993). In particular, for each pair (j,k) with $j<k$ of consumption goods we consider the relation

$$b_{\langle k\rangle,t} - b_{\langle j\rangle,t} = \eta\kappa_{(j,k)} + \eta(p_{j,t} - p_{k,t}) + \left(\sum_{\ell=-l}^{l} \varphi_{(j,k),\ell} L^{\ell} \right) \Delta(p_{j,t} - p_{k,t}) + \zeta_{(j,k),t}, \tag{B.5}$$

where $\kappa_{(j,k)}$ denotes a constant, Δ denotes the first difference, i.e., $\Delta x_t = x_t - x_{t-1}$, and L denotes the lag operator. Following Yogo (2006) we use three leads and lags (that means $l = 3$), but also run specifications with one, two, and four leads and lags. We find that the estimated substitution elasticity parameter and measures of relative goodness-of-fit are not materially dependent on the lag structure.

Similar to the procedure that does not consider any leads or lags, described in Section 2.3, we multiply Equation (B.5) by $1/\eta$ and estimate the inverse of the intratemporal elasticity of substitution. For all pairs (j,k) with $j<k$, we define

$$\varepsilon_{(j,k),t} \equiv \frac{\zeta_{(j,k),t}}{\eta} = p_{k,t} - p_{j,t} + \frac{1}{\eta}\left(b_{\langle k\rangle,t} - b_{\langle j\rangle,t} \right) - \left(\sum_{\ell=-l}^{l} \tilde{\varphi}_{(j,k),\ell} L^{\ell} \right) \Delta(p_{j,t} - p_{k,t}) - \kappa_{(j,k)}, \tag{B.6}$$

where $\tilde{\varphi}_{(j,k),\ell} = \frac{\varphi_{(j,k),\ell}}{\eta}$ for $\ell = -l,\ldots,l$. We use the following sample moment conditions for our GMM

[21] Note that the alternative moment conditions $\mathbb{E}_T[\zeta_{(j,k),t}] = 0$ and $\mathbb{E}_T[\zeta_{(j,k),t}(p_{j,t} - p_{k,t})] = 0$ can be set to zero by choosing $\eta = 0$ when the basic goods j and k are in the same bundle. Thus, the alternative GMM estimator based on these moment conditions can produce a downward-biased point estimate of η in the presence of model misspecification.

estimator:

$$g_T \begin{pmatrix} \eta^{-1} \\ \kappa_{(1,2)} \\ \tilde{\varphi}_{(1,2),-l} \\ \dots \\ \tilde{\varphi}_{(1,2),l} \\ \kappa_{(1,3)} \\ \dots \\ \tilde{\varphi}_{(N-1,N),l} \end{pmatrix} = \mathbb{E}_T \begin{bmatrix} \varepsilon_{(1,2),t} \\ \varepsilon_{(1,2),t}(p_{1,t} - p_{2,t}) \\ \varepsilon_{(1,2),t} L^{-l} \Delta(p_{1,t} - p_{2,t}) \\ \dots \\ \varepsilon_{(1,2),t} L^{l} \Delta(p_{1,t} - p_{2,t}) \\ \varepsilon_{(1,3),t} \\ \dots \\ \varepsilon_{(N-1,N),t} L^{l} \Delta(p_{N-1,t} - p_{N,t}) \end{bmatrix}. \tag{B.7}$$

All in all, our GMM estimator uses $(3+2l)\binom{N}{2}$ moment restrictions to estimate $(2+2l)\binom{N}{2}+1$ parameters.

C Robustness of consumption good bundling

After analyzing the substitution elasticities between minor categories within single major categories of consumption goods and services, our analysis in Table 3, we move on to jointly analyzing minor categories in Table 4. In Table 4, we consider all durable goods as perfect substitutes of one another. For simplicity, we do not consider recreational goods and vehicles as a separate good, although Table 3 suggests that it is optimal to do so.

Table C.1 shows the corresponding results when starting with a bundle containing *Food* and *Other nondurable goods* (denoted Nfo), clothing (Nc), energy goods (Ne), a bundle containing *Motor vehicles and parts*, *Furnishings and durable household equipment*, and *Other durable goods* ($Dmfo$), *Recreational goods and vehicles* (Dr), and *Services* (S) as primitive goods. The most likely partition consists of four bundles: First, *Food*, *Other nondurable goods*, and *Services*, second *Clothing and footware*, *Motor vehicles and parts*, *Furnishings and durable household equipment*, and *Other durable goods*, third *Recreational goods and vehicles*, and fourth *Energy goods*. Thus, it is exactly as the optimal partition shown in Table 4 in the main text, except that *Recreational goods and vehicles* are now separated from the remaining durable goods.

D Further sensitivity analyses regarding the parameter estimation

Instead of a free estimation of all of the preference parameters, we fix the IES to values that are commonly used in the literature and estimate the remaining parameters. In Table 5, we choose $\psi = 1.5$, in line with Bansal and Yaron (2004) and large parts of the macro asset pricing literature. To study the sensitivity to the chosen IES, we now choose one very high value for the IES ($\psi = 10$). Bansal and Yaron (2004) point out that an IES above one is crucial to generate a plausible time series behavior of the price dividend ratio of the aggregate stock market. Other authors, for example Hall (1988) have found IES estimates below one. To account for these diverging views, we also include an IES of 0.5.

Table C.1: **Parameter estimates, likelihood, and average RMSE**

rnk(LL)	Partition	$\widehat{\eta^{-1}}$	se	LL	RMSE
Panel A: Three leads and lags					
1	$Nfo, S/Nc, Dmfo/Ne/Dr$	1.21	(0.07)	200.46	0.25
2	$Nfo, S/Nc/Ne/Dmfo/Dr$	1.22	(0.07)	−103.06	0.28
3	$Nfo, Nc, S/Ne/Dmfo/Dr$	1.16	(0.05)	−269.72	0.28
4	$Nfo/Nc, Dmfo/Ne/Dr/S$	1.19	(0.06)	−285.56	0.28
5	$Nfo/Nc/Ne/Dmfo, S/Dr$	1.20	(0.06)	−476.22	0.31
7	$Nfo/Nc/Ne/Dmfo/Dr/S$	1.20	(0.06)	−546.31	0.31
105	$Nfo, Nc, Ne, S/Dmfo, Dr$	1.98	(0.55)	−2342.30	0.63
167	$Nfo, Nc, Ne, Dmfo, Dr, S$	–	–	−2703.15	0.73
Panel B: No leads and lags					
1	$Nfo, S/Nc, Dmfo/Ne/Dr$	1.21	(0.04)	1025.32	0.20
2	$Nfo, Ne, S/Nc, Dmfo/Dr$	1.40	(0.04)	959.87	0.20
3	$Nfo, S/Nc/Ne/Dmfo/Dr$	1.21	(0.04)	838.37	0.21
4	$Nfo, Ne, S/Nc/Dmfo/Dr$	1.39	(0.04)	748.49	0.22
5	$Nfo/Nc, Dmfo/Ne/Dr/S$	1.19	(0.04)	476.23	0.22
9	$Nfo/Nc/Ne/Dmfo/Dr/S$	1.19	(0.04)	252.45	0.24
97	$Nfo, Nc, Ne, S/Dmfo, Dr$	2.43	(0.13)	−1630.95	0.47
131	$Nfo, Nc, Ne, Dmfo, Dr, S$	–	–	−1962.63	0.55

The primitive consumption categories are *food and beverages purchased for off-premises consumption* (Nf), *clothing and footwear* (Nc), *gasoline and other energy goods* (Ne), *other nondurable goods* (No), *Motor vehicles and parts* (Dm), *Furnishings and durable household equipment* (Df), *Recreational goods and vehicles* (Dr), *Other durable goods* (Do), and *services* (S). Primitive consumption categories belonging to the same bundle are separated by commas, and the different bundles are separated by slashes. Nfo and $Dmfo$ are short for Nf, No and Dm, Df, Do, respectively. se denotes the standard error of $\widehat{\eta^{-1}}$, LL is the log likelihood, and RMSE is the average root mean squared error, i.e., the average of $\widehat{\sigma}_{(j,k)}$ as defined in Section 2.3. There are 203 possible ways to bundle these six goods. The table only shows the partition with the highest likelihood, the partition that separates durable goods from all other goods, and the partitions placing all goods in separate bundles/in one bundle. Panel A shows results of the baseline specification with three leads and lags, while panel B shows results of the alternative specification without any leads and lags. All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

Table D.1: **Estimating preference parameters: Alternative values of IES**

Partition	ψ^{-1}	δ	γ	η^{-1}	a_2/a_1	a_3/a_1	MIRP	R^2	MAE
$Nf, No, S/Nc, D/Ne$	1/10	0.0117	30.81	0.99	0.12	4.29	0.0186	0.54	0.0041
		(0.0018)	(10.66)	(0.16)	(0.05)	(0.73)	(0.0057)	(0.18)	(0.0012)
	2	−0.0048	−32.60	0.99	0.12	4.27	0.0159	0.43	0.0049
		(0.0022)	(22.66)	(0.13)	(0.05)	(0.76)	(0.0062)	(0.18)	(0.0013)
$Nf, Nc, Ne, No, S/D$	1/10	0.0138	26.66	1.58	9.54		0.0040	0.09	0.0061
		(0.0424)	(42.61)	(0.43)	(4.58)		(0.0036)	(0.11)	(0.0011)
	2	−0.0042	−27.32	1.58	9.44		0.0057	0.09	0.0062
		(0.0376)	(20.99)	(0.43)	(4.58)		(0.0036)	(0.07)	(0.0013)

Point estimates of the preference parameters with bootstrapped standard errors in parentheses. The inverse IES ψ^{-1} is fixed to values of 1/10 and 2. We also report the model-implied risk premium (MIRP), the cross-sectional R^2 and the mean absolute pricing error (MAE) for the returns on a 3-month Treasury Bill and a set of 18 portfolios sorted on size, book-to-market ratio, asset growth, and operating profitability. The primitive consumption categories are *food and beverages purchased for off-premises consumption* (Nf), *clothing and footwear* (Nc), *gasoline and other energy goods* (Ne), *other nondurable goods* (No), *services* (S), and *durable goods* (D). Primitive consumption categories belonging to the same bundle are separated by commas, and the different bundles are separated by slashes. All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

Table D.1 shows the point estimates and model performance statistics. When $\psi = 10$, the results are very similar to those with $\psi = 1.5$ reported in Panel A of Table 5. Estimates of the relative risk aversion and time preference parameters are higher compared to the case with $\psi = 1.5$, but the remaining parameters and also the model performance statistics do not change materially.

When $\psi < 1$, the model has relatively similar performance in terms of fitting asset prices, but more difficulty producing economically reasonable parameter estimates. The model fit with an R^2 of 0.43 and mean absolute pricing error of 49 basis points per quarter represents only a modest decline relative to the other two cases. Further, the model-implied risk premium of 1.59% per quarter is also reasonable. However, the point estimates of the preference parameters δ and γ are negative.

Instead of fixing the IES, we also fix γ at a value of 10 and estimate the remaining preference parameters, especially the inverse IES. The results, shown in Table D.2, are very plausible. In case of the first model specification, the inverse IES is estimated at 0.73 with a standard error of about 0.12, so that the value of 1.5^{-1}, suggested by Bansal and Yaron (2004), cannot be rejected. The second specification yields a similar IES. Again, the model's explanatory power for the cross-section of expected returns is lower relative to the specification which considers energy as a separate bundle.

To investigate the impact of the steady state wealth consumption ratio, we vary κ and repeat the estimation exercise from Section 3.2. We fix the IES to 1.5, but our conclusions are similar for other values. Table D.3 shows the results for steady state values of 25, 83, and 150. We find that the parameter estimates and model performance statistics are barely affected by the change in κ. The

Table D.2: **Estimating preference parameters: Risk aversion fixed**

Partition	ψ^{-1}	δ	γ	η^{-1}	a_2/a_1	a_3/a_1	MIRP	R^2	MAE
$Nf, No, S/Nc, D/Ne$	0.73	0.0064	10	1.00	0.13	4.28	0.0178	0.51	0.0044
	(0.12)	(0.0027)		(0.18)	(0.06)	(1.34)	(0.0060)	(0.18)	(0.0013)
$Nf, Nc, Ne, No, S/D$	0.71	0.0082	10	1.58	9.53		0.0049	0.09	0.0061
	(0.24)	(0.0035)		(0.33)	(4.57)		(0.0067)	(0.15)	(0.0012)

Point estimates of the preference parameters. Bootstrapped standard errors are in parentheses. The coefficient of relative risk aversion γ is fixed at 10. We also report the model-implied risk premium (MIRP), the cross-sectional R^2, and the mean absolute pricing error (MAE). The primitive consumption categories are *food and beverages purchased for off-premises consumption* (Nf), *clothing and footwear* (Nc), *gasoline and other energy goods* (Ne), *other nondurable goods* (No), *services* (S), and *durable goods* (D). Primitive consumption categories belonging to the same bundle are separated by commas, and the different bundles are separated by slashes. All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

only exceptions are the point estimates and standard errors of δ. Changing κ ceteris paribus changes the level of the IMRS. This change is counterbalanced by a change in δ.

We also estimate the model placing more weight on the Euler equation conditions than the intratemporal relation between price and consumption differences, with the goal of permitting the model to have the best chance at explaining cross-sectional variation in average returns. Specifically, the intratemporal moment conditions are given weight 0.001, as opposed to 1.0 in Section 3.

Results of this estimation are presented in Table D.4. In the three-bundle case, models with ψ^{-1} fixed at 1/10 and 2/3 fare about equally well in fitting cross-sectional variation in equity returns, with cross-sectional R^2 of 0.60, representing a modest increase relative to the results in Table 5. The fit is achieved with modest risk aversion, although the standard errors suggest that we cannot reject the hypothesis that the estimate is zero. The improvement comes at the cost of a larger estimate of η^{-1} and the virtual elimination of the (Nf, No, S) subset from the priced consumption bundle.

The source of model fit is worthy of further discussion. As in Bansal and Yaron (2004), separation of risk aversion and elasticity of intertemporal substitution allow the model to match the risk-free rate quite well; the mean of the stochastic discount factor pins down this moment. As explained in Section 3.2, the risk-free rate thereby identifies δ. To satisfy the other Euler equations the model needs to generate a large risk premium on the equity test assets relative to the risk-free rate. The level of this risk premium thus identifies the risk aversion coefficient γ. The term in parentheses in Equation (14) is positively related to the test asset returns, because the return on the wealth portfolio R_w is. This implies that θ must be negative to match the risk premium and, since $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$, γ is estimated at a value above 1 whenever ψ is above 1 and vice versa.

Comparing the three-bundle model (separating energy consumption) with the two-bundle case, we find that separation of the more volatile energy consumption bundle allows the model to achieve the level of the risk premium with lower risk aversion. At the same time, the greater cross-sectional correlation of returns with energy consumption exposures generate a cross-sectional risk premium.

Table D.3: **Parameter estimates**

Partition	κ	δ	γ	η^{-1}	a_2/a_1	a_3/a_1	MIRP	R^2	MAE
$Nf, No, S/Nc, D/Ne$	1/25	0.0141	12.43	1.00	0.13	4.28	0.0182	0.51	0.0043
		(0.0016)	(4.23)	(0.18)	(0.06)	(0.99)	(0.0057)	(0.18)	(0.0012)
	1/83	0.0069	12.37	1.00	0.13	4.28	0.0181	0.51	0.0043
		(0.0016)	(4.90)	(0.16)	(0.05)	(0.73)	(0.0060)	(0.18)	(0.0012)
	1/150	0.0055	12.37	1.00	0.13	4.28	0.0181	0.51	0.0043
		(0.0015)	(4.20)	(0.18)	(0.06)	(0.99)	(0.0057)	(0.18)	(0.0012)
$Nf, Nc, Ne, No, S/D$	1/25	0.0159	11.14	1.58	9.53		0.0049	0.09	0.0061
		(0.0174)	(13.95)	(0.40)	(3.56)		(0.0036)	(0.09)	(0.0012)
	1/83	0.0086	11.20	1.58	9.54		0.0049	0.09	0.0061
		(0.0381)	(14.63)	(0.43)	(4.58)		(0.0051)	(0.12)	(0.0011)
	1/150	0.0072	11.21	1.58	9.54		0.0049	0.09	0.0061
		(0.0153)	(14.38)	(0.40)	(3.56)		(0.0037)	(0.10)	(0.0012)

This table shows point estimates of the preference parameters, together with bootstrapped standard errors (below the point estimates). The inverse IES ψ^{-1} is fixed at 2/3. We set κ, the steady state consumption-to-wealth ratio, to values of 1/25, 1/83, and 1/150, respectively. We also report the model-implied risk premium (MIRP), the cross-sectional R^2, and the mean absolute pricing error (MAE). The primitive consumption categories are *food and beverages purchased for off-premises consumption* (Nf), *clothing and footwear* (Nc), *gasoline and other energy goods* (Ne), *other nondurable goods* (No), *services* (S), and *durable goods* (D). Primitive consumption categories belonging to the same bundle are separated by commas, and the different bundles are separated by slashes. All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

In the specifications with two bundles, energy consumption is not considered separately from consumption of other nondurable goods and services. As a result, the model does not generate sufficient volatility in the stochastic discount factor to generate either a market or cross-sectional risk premium.

The same effect can be observed again when looking at the three-bundle model, but using the bundle (Nf, No, S) as the numeraire. The results of the estimation are shown in Table D.5. The point estimates are qualitatively similar to those in Table 5. We find higher point estimates of the risk aversion coefficient in case $\psi > 1$ and more negative estimates in case $\psi < 1$. Moreover, the pricing performance is worse compared to the results in Table 5, where we use energy as the numeraire.

Table D.4: **Estimating preference parameters: Focus on asset prices**

Partition	ψ^{-1}	δ	γ	η^{-1}	a_2/a_1	a_3/a_1	MIRP	R^2	MAE
$Nf, No, S/Nc, D/Ne$	1/10	0.0162	15.17	3.23	0.00	0.49	0.0176	0.61	0.0037
		(0.0039)	(8.00)	(0.85)	(0.08)	(0.97)	(0.0052)	(0.18)	(0.0011)
	2/3	0.0115	6.16	3.45	0.00	0.40	0.0176	0.60	0.0037
		(0.0023)	(11.51)	(1.15)	(0.15)	(1.01)	(1.0067)	(0.20)	(0.0044)
	2	−0.0000	−13.78	4.02	0.00	0.23	0.0174	0.59	0.0037
		(0.0025)	(7.39)	(0.76)	(0.06)	(0.53)	(0.0063)	(0.26)	(0.0051)
$Nf, Nc, Ne, No, S/D$	1/10	0.0962	−4.48	20.32	0.00		0.0120	0.36	0.0053
		(0.0426)	(8.21)	(3.00)	(0.06)		(0.0119)	(0.95)	(0.0029)
	2/3	0.0089	−1.08	19.88	0.00		0.0117	0.36	0.0053
		(0.0102)	(2.19)	(5.17)	(0.25)		(0.0072)	(0.51)	(0.0016)
	2	0.0792	7.38	20.33	0.00		0.0118	0.36	0.0053
		(0.0203)	(3.77)	(4.67)	(0.25)		(0.0041)	(0.18)	(0.0055)

Point estimates of the preference parameters. Bootstrapped standard errors are in parentheses. The weight on the intratemporal moment conditions is set to 0.001. The inverse IES ψ^{-1} is fixed at values of 10^{-1}, 1.5^{-1}, and 0.5^{-1}. We also report the model-implied risk premium (MIRP), the cross-sectional R^2 and the mean absolute pricing error (MAE). The primitive consumption categories are *food and beverages purchased for off-premises consumption* (Nf), *clothing and footwear* (Nc), *gasoline and other energy goods* (Ne), *other nondurable goods* (No), *services* (S), and *durable goods* (D). Primitive consumption categories belonging to the same bundle are separated by commas, and the different bundles are separated by slashes. All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

E Derivation of the approximate linear factor structure

Taking the logarithm of the stochastic discount factor in Equation (10) yields

$$m_{t+1} = -\delta - \frac{1}{\eta}\log\left(\frac{B_{*,t+1}}{B_{*,t}}\right) - \left(\frac{1}{\psi} - \frac{1}{\eta}\right)\log\left(\frac{u_{t+1}}{u_t}\right) - \left(\gamma - \frac{1}{\psi}\right)\log\left(\tilde{V}_{t+1}\right), \tag{E.1}$$

where $\tilde{V}_{t+1} = \frac{V_{t+1}}{(\mathbb{E}_t[V_{t+1}^{1-\gamma}])^{\frac{1}{1-\gamma}}}$. According to Equation (2), innovations in $\tilde{V}_{t+1}$ directly depend on innovations in u_{t+1} and innovations in the continuation value $\mathbb{E}_{t+1}[V_{t+2}^{1-\gamma}]$. We separate the direct effect of $\log\left(\frac{u_{t+1}}{u_t}\right)$ on $\log(\tilde{V}_{t+1})$ by decomposing $\log(\tilde{V}_{t+1})$ as

$$\log(\tilde{V}_{t+1}) = \left.\frac{\partial \log(\tilde{V}_{t+1})}{\partial \log\left(\frac{u_{t+1}}{u_t}\right)}\right|_{s_0} \log\left(\frac{u_{t+1}}{u_t}\right) + \log(\widehat{V}_{t+1}), \tag{E.2}$$

Table D.5: **Estimating preference parameters: Food/other/services as numeraire**

Partition	ψ^{-1}	δ	γ	η^{-1}	a_2/a_1	a_3/a_1	MIRP	R^2	MAE
$Nf, No, S/Nc, D/Ne$	1/10	0.0086	62.07	0.97	0.14	4.42	0.0185	−0.14	0.0069
		(0.0010)	(17.98)	(0.19)	(0.11)	(1.25)	(0.0041)	(0.42)	(0.0019)
	2/3	0.0043	24.78	0.97	0.14	4.42	0.0187	−0.15	0.0069
		(0.0010)	(9.66)	(0.21)	(0.11)	(1.30)	(0.0044)	(0.40)	(0.0016)
	2	−0.0077	−80.50	0.96	0.14	4.44	0.0190	−0.23	0.0071
		(0.0013)	(17.30)	(0.22)	(0.23)	(1.19)	(0.0046)	(0.40)	(0.0025)

Point estimates of the preference parameters. Bootstrapped standard errors are in parentheses. Consumption of food, other nondurable goods, and services serves as the numeraire. The inverse IES ψ^{-1} is fixed at values of 10^{-1}, 1.5^{-1}, and 0.5^{-1}. We also report the model-implied risk premium (MIRP), the cross-sectional R^2 and the mean absolute pricing error (MAE). The primitive consumption categories are *food and beverages purchased for off-premises consumption* (Nf), *clothing and footwear* (Nc), *gasoline and other energy goods* (Ne), *other nondurable goods* (No), *services* (S), and *durable goods* (D). Primitive consumption categories belonging to the same bundle are separated by commas, and the different bundles are separated by slashes. All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

where $\log(\widehat{V}_{t+1})$ denotes the variation of $\tilde{V}_{t+1}$ that remains after taking out the first order effect of the growth in u. It can be thought of as innovations due to changes in the state variables. The derivative is given by

$$\frac{\partial \log(\tilde{V}_{t+1})}{\partial \log\left(\frac{u_{t+1}}{u_t}\right)} = (1-\delta)\left(\frac{u_{t+1}}{V_{t+1}}\right)^{1-\frac{1}{\psi}} \tag{E.3}$$

This term varies around one and we evaluate the derivative at a state s_0 such that it is exactly equal to one. Substituting this relation in Equation (E.1) gives

$$m_{t+1} = -\delta - \frac{1}{\eta}\log\left(\frac{B_{*,t+1}}{B_{*,t}}\right) - \left(\gamma - \frac{1}{\eta}\right)\log\left(\frac{u_{t+1}}{u_t}\right) - \left(\gamma - \frac{1}{\psi}\right)\log\left(\widehat{V}_{t+1}\right), \tag{E.4}$$

We now use a first order Taylor approximation of

$$\log(u_t) = \frac{1}{1-\frac{1}{\eta}}\log\left(\sum_{i=1}^{M} a_i B_{i,t}^{1-\eta^{-1}}\right)$$

around $\bar{b}_i = \mathbb{E}[\log(B_{i,t})]$:

$$\log\left(\sum_{i=1}^{M} a_i \exp((1-\eta^{-1})b_{i,t})\right) \approx \log\left(\sum_{i=1}^{M} a_i \exp((1-\eta^{-1})\bar{b}_i)\right) + \left(1-\frac{1}{\eta}\right)\sum_{i=1}^{M} \underbrace{\frac{a_i \exp((1-\eta^{-1})\bar{b}_{i,t})}{\sum_{i=1}^{M} a_i \exp((1-\eta^{-1})\bar{b}_{i,t})}}_{=:\tilde{a}_i}(b_{i,t}-\bar{b}_i) \tag{E.5}$$

$\tilde{a}_i$ is a weight of bundle i and close to a_i if η is close to one. Substituting Equation (E.5) into Equation (E.4) yields the approximation

$$m_{t+1} \approx -\delta - \left(\tilde{a}_*\gamma + (1-\tilde{a}_*)\frac{1}{\eta}\right)\log\left(\frac{B_{*,t+1}}{B_{*,t}}\right) - \sum_{i\neq *}\left(\tilde{a}_i\gamma - \frac{\tilde{a}_i}{\eta}\right)\log\left(\frac{B_{i,t+1}}{B_{i,t}}\right) - \left(\gamma - \frac{1}{\psi}\right)\log\left(\widehat{V}_{t+1}\right).$$

Using a first-order Taylor approximation of $\frac{\exp(m_{t+1})}{\mathbb{E}[\exp(m_{t+1})]}$ around $\mathbb{E}[m_{t+1}]$ gives

$$\begin{aligned}
-\frac{\exp(m_{t+1})}{\mathbb{E}[\exp(m_{t+1})]} &\approx -\frac{\exp(\mathbb{E}[m_{t+1}])}{\mathbb{E}[\exp(m_{t+1})]} - \frac{\exp(\mathbb{E}[m_{t+1}])}{\mathbb{E}[\exp(m_{t+1})]}\Big(m_{t+1} - \mathbb{E}[m_{t+1}]\Big) \\
&\approx \Lambda_0 + \sum_{i=1}^{M}\Lambda_i \log\left(\frac{B_{i,t+1}}{B_{i,t}}\right) + \Lambda_v \log\left(\widehat{V}_{t+1}\right)
\end{aligned}$$

where the coefficients Λ_i $(i = 0, \dots, M)$ and Λ_v are given as

$$\begin{aligned}
\Lambda_* &= \tilde{a}_*\gamma + (1-\tilde{a}_*)\frac{1}{\eta}, \\
\Lambda_i &= \tilde{a}_i\gamma - \frac{\tilde{a}_i}{\eta}, \text{ for } i \neq *, \text{ and} \\
\Lambda_v &= \gamma - \frac{1}{\psi}.
\end{aligned} \tag{E.6}$$

Equation (9) holds for all assets j such that we can alternatively write

$$0 = \mathbb{E}\left[M_{t+1}(R_{j,t+1} - R_{f,t+1})\right] = Cov(M_{t+1}, R_{j,t+1} - R_{f,t+1}) + \mathbb{E}[M_{t+1}]\mathbb{E}[R_{j,t+1} - R_{f,t+1}] \tag{E.7}$$

which implies the approximate linear factor structure

$$\mathbb{E}[R_{j,t+1} - R_{f,t+1}] = Cov(-\frac{M_{t+1}}{\mathbb{E}[M_{t+1}]}, R_{j,t+1} - R_{f,t+1}) \approx \sum_{i=1}^{M}\lambda_i\beta_{i,j} + \lambda_v\beta_{v,j}. \tag{E.8}$$

Here, we use the following notation in line with convention in the literature:

$$\beta_{i,j} = \frac{Cov\left(R_{j,t+1} - R_{f,t+1}, \log(B_{i,t+1}/B_{i,t})\right)}{Var\left(\log(B_{i,t+1}/B_{i,t})\right)}$$

and

$$\beta_{v,j} = \frac{Cov\left(R_{j,t+1} - R_{f,t+1}, \log(\tilde{V}_{t+1})\right)}{Var\left(\log(\tilde{V}_{t+1})\right)}$$

are the exposures of the return on asset j to the log growth rate in consumption bundle i and the value function innovation, respectively. λ_i for $i \in \{1, \ldots, M, v\}$ are the market prices of risks regarding the different consumption bundles and the return on wealth. The approximation in Equation (E.8) makes use of Equation (E.6) with $\lambda_i = \Lambda_i Var\left(\log(B_{i,t+1}/B_{i,t})\right)$ for $i = 1, \ldots, M$ and $\lambda_v = \Lambda_v Var\left(\log(\tilde{V}_{t+1})\right)$, respectively.

For the interpretation of the market prices of risk, note that the sum of the market prices of consumption risks is always equal to the risk aversion coefficient γ of the consumer. In the case of perfect intratemporal substitutability between bundles ($\eta^{-1} = 0$), the share of every bundle i is equal to its weighting $\tilde{a}_i$. Here, the consumer is indifferent between different bundles, so positive growth in any bundle is (equally) good news to them. With a lower intratemporal substitution elasticity, more of the market price of risk is moved to the numeraire bundle. Now, the consumer cannot substitute either good to increase utility, but they need some consumption of every bundle, especially also the numeraire.

The market price of shocks in $\widehat{V}$ is positive when the relative risk aversion coefficient exceeds the inverse of the intertemporal elasticity of substitution, a situation often referred to as a "preference for early resolution of uncertainty". We could for example think of in "long-run" consumption growth state variable as in Bansal and Yaron (2004). A positive shock in that state variable leads to a positive innovation in $\widehat{V}$, which has a positive market price of risk if the consumer prefers early resolution of uncertainty.

Taking the logarithm of the alternative representation of the stochastic discount factor in Equation (12) yields

$$m_{t+1} = -\delta\theta - \frac{\theta}{\eta} \log\left(\frac{B_{*,t+1}}{B_{*,t}}\right) - \left(\frac{\theta}{\psi} - \frac{\theta}{\eta}\right) \log\left(\frac{u_{t+1}}{u_t}\right) - (1-\theta) r_{w,t+1}. \tag{E.9}$$

Similar approximations as above lead to

$$m_{t+1} \approx -\theta\delta - \theta\left(\frac{\tilde{a}_*}{\psi} + \frac{1-\tilde{a}_*}{\eta}\right) \log\left(\frac{B_{*,t+1}}{B_{*,t}}\right) - \theta \sum_{i \neq *} \left(\frac{\tilde{a}_i}{\psi} - \frac{\tilde{a}_i}{\eta}\right) \log\left(\frac{B_{i,t+1}}{B_{i,t}}\right) - (1-\theta) r_{w,t+1}, \tag{E.10}$$

which again leads to an alternative representation with

$$\mathbb{E}[R_{j,t+1} - R_{f,t+1}] = Cov\left(-\frac{M_{t+1}}{\mathbb{E}[M_{t+1}]}, R_{j,t+1} - R_{f,t+1}\right) \approx \sum_{i=1}^{M} \lambda_i^r \beta_{i,j} + \lambda_v^r \beta_{v,j}. \tag{E.11}$$

where $\lambda_i^r = \Lambda_i^r Var\left(\log(B_{i,t+1}/B_{i,t})\right)$ for $i = 1, \ldots, M$ and $\lambda_w^r = \Lambda_w^r Var\left(r_{w,t+1}\right)$. The Λ's are given by

$$\begin{aligned}
\Lambda_*^r &= \theta\left(\frac{\tilde{a}_*}{\psi} + \frac{1-\tilde{a}_*}{\eta}\right), \\
\Lambda_i^r &= \theta\left(\frac{\tilde{a}_i}{\psi} - \frac{\tilde{a}_i}{\eta}\right), \text{ for } i \neq *, \text{ and} \\
\Lambda_v^r &= 1-\theta.
\end{aligned} \tag{E.12}$$

It is important to keep in mind here that we have not "netted out" the effects of consumption growth rates as in the market prices of risks in Equation (E.6). In cases where $\gamma > 1 > \frac{1}{\psi}$, that means $\theta < 0$, Λ_*^r is negative, although the market price of risk Λ_* is always positive.

The explanation of this seeming contradiction is that r_w innovations also depend on consumption growth innovations. This is intuitive: Consumption can be thought of as the dividends on the claim on aggregate wealth. More formally, Equation (11) shows the exact relation between returns on the wealth claim and consumption growth.

F Further results related to the linear factor model

The following tables provide additional results for the linear factor models. We estimate the different candidate models using 25 portfolios sorted by size and the book-to-market ratio (Table F.1), using 25 portfolios sorted by size and investment (Table F.2), and 25 portfolios sorted by size and operating profitability (Table F.3). Table F.4 shows results for a model where we consider the growth rate of consumption of recreational goods and durables as a separate factor.

Table F.1: **Market prices of risks (25 size and book-to-market sorted portfolios)**

	Our model				Other consumption models			CAPM	Fama/French	
	1	2	3	4	5	6	7	8	9	10
Ne	2.03** [2.31]	2.10** [2.50]	2.10** [2.24]	2.14** [2.32]						0.21 [0.54]
Nf, No, S	0.16 [0.52]	0.27 [1.64]								
Nc, D	0.21 [0.71]	0.23 [0.78]								
Nf, Nc, Ne, No, S					0.09 [0.45]	0.52** [2.38]	0.52** [2.10]			
D							0.61 [1.44]			
MKT		0.19 [0.11]		0.03 [0.02]		0.27 [0.17]	0.30 [0.17]	-0.31 [−0.29]	-0.61 [−0.48]	-0.48 [−0.40]
SMB									0.71 [1.83]	0.71* [1.83]
HML									1.06*** [2.65]	1.05*** [2.62]
CMA									0.37 [0.84]	0.38 [0.85]
RMW									0.99** [2.03]	0.98** [1.99]
const	1.66 [1.47]	1.88 [1.19]	1.43 [1.38]	2.00 [1.33]	1.85** [2.32]	2.27 [1.63]	2.08 [1.30]	2.67*** [2.94]	2.18** [1.99]	2.06** [1.98]
MAE	0.37	0.36	0.38	0.37	0.54	0.47	0.44	0.55	0.23	0.22
R^2	45.86	46.96	43.61	46.00	1.59	17.22	24.64	0.83	79.36	79.43

Market prices of risk estimates in a linear factor model. An intercept is included in the cross-sectional regression. Test assets are 25 portfolios sorted with respect to size and book-to-market ratio. We use portfolio returns in excess of the cumulative 3-month Treasury bill rate. Root mean squared errors (RMSE) and R^2s are expressed in percentage points. The primitive consumption categories are *food and beverages purchased for off-premises consumption* (Nf), *clothing and footwear* (Nc), *gasoline and other energy goods* (Ne), *other nondurable goods* (No), *services* (S), and *durable goods* (D). All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

Table F.2: **Market prices of risks (25 size and investment sorted portfolios)**

	Our model				Other consumption models			CAPM	Fama/French	
	1	2	3	4	5	6	7	8	9	10
Ne	1.81^{**} [1.96]	1.84^{***} [2.60]	1.70^{**} [2.10]	1.73^{**} [2.30]						0.50 [1.21]
Nf, No, S	0.04 [0.13]	0.07 [0.36]								
Nc, D	-0.15 [−0.87]	-0.15 [−0.86]								
Nf, Nc, Ne, No, S					0.05 [0.27]	0.19 [1.64]	0.13 [0.97]			
D							0.32^{*} [1.70]			
MKT		0.05 [0.03]		0.17 [0.12]		0.21 [0.19]	0.00 [0.00]	-0.01 [−0.01]	1.11 [0.79]	1.60 [1.19]
SMB									0.47 [1.08]	0.50 [1.15]
HML									1.71^{**} [2.09]	1.46 [1.64]
CMA									0.79^{***} [2.72]	0.78^{***} [2.68]
RMW									0.36 [0.67]	0.46 [0.85]
const	2.01^{*} [1.95]	2.05^{*} [1.58]	1.62^{*} [1.79]	1.93^{*} [1.61]	2.05^{***} [2.86]	2.18^{**} [2.50]	2.27^{**} [2.42]	2.34^{***} [3.00]	0.66 [0.53]	0.19 [0.16]
MAE	0.35	0.35	0.36	0.36	0.49	0.49	0.47	0.50	0.21	0.19
R^2	42.55	42.63	39.08	39.87	0.60	2.46	7.37	0.00	77.35	78.10

Market prices of risk estimates in a linear factor model. An intercept is included in the cross-sectional regression. Test assets are 25 portfolios sorted with respect to size and investment. We use portfolio returns in excess of the cumulative 3-month Treasury bill rate. Root mean squared errors (RMSE) and R^2s are expressed in percentage points. The primitive consumption categories are *food and beverages purchased for off-premises consumption* (Nf), *clothing and footwear* (Nc), *gasoline and other energy goods* (Ne), *other nondurable goods* (No), *services* (S), and *durable goods* (D). All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

Table F.3: **Market prices of risks (25 size and profitability sorted portfolios)**

	Our model				Other consumption models			CAPM	Fama/French	
	1	2	3	4	5	6	7	8	9	10
Ne	2.02 [1.49]	1.62** [1.97]	1.89* [1.84]	1.79* [1.94]						-0.16 [−0.28]
Nf, No, S	0.20 [0.51]	-0.01 [−0.03]								
Nc, D	-0.18 [−0.61]	-0.25 [−1.10]								
Nf, Nc, Ne, No, S					0.29 [1.01]	0.07 [0.52]	0.11 [0.73]			
D							-0.21 [−1.21]			
MKT		1.00 [0.64]		1.21 [0.81]		1.39 [1.18]	1.84 [1.47]	1.29 [1.15]	0.90 [0.78]	0.61 [0.54]
SMB									0.64 [1.56]	0.64 [1.58]
HML									0.42 [0.68]	0.38 [0.61]
CMA									-0.47 [−0.94]	-0.57 [−1.04]
RMW									0.66** [2.30]	0.66** [2.30]
const	0.97 [0.66]	0.88 [0.62]	1.48 [1.52]	0.68 [0.51]	0.65 [0.56]	0.69 [0.72]	0.31 [0.29]	0.77 [0.85]	0.87 [0.89]	1.16 [1.21]
MAE	0.28	0.29	0.29	0.29	0.46	0.45	0.42	0.45	0.15	0.14
R^2	60.73	62.93	53.92	57.64	9.77	11.88	17.27	11.80	89.27	89.50

Market prices of risk estimates in a linear factor model. An intercept is included in the cross-sectional regression. Test assets are 25 portfolios sorted with respect to size and operating profitability. We use portfolio returns in excess of the cumulative 3-month Treasury bill rate. Root mean squared errors (RMSE) and R^2s are expressed in percentage points. The primitive consumption categories are *food and beverages purchased for off-premises consumption* (Nf), *clothing and footwear* (Nc), *gasoline and other energy goods* (Ne), *other nondurable goods* (No), *services* (S), and *durable goods* (D). All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

Table F.4: **Market prices of risks (separating recreational goods/vehicles)**

	All 75		Size/Book-to-market		Size/Investment		Size/Profitability	
	1	2	3	4	5	6	7	8
Ne	1.93*	1.88**	1.83	1.77*	1.82**	1.84**	2.10	1.67**
	[1.90]	[2.45]	[1.63]	[1.75]	[2.07]	[2.60]	[1.54]	[2.05]
Nf, No, S	0.18	0.14	0.25	0.18	0.04	0.06	0.28	0.05
	[0.67]	[1.27]	[0.71]	[0.92]	[0.16]	[0.31]	[0.73]	[0.26]
Nc, Dm, Df, Do	0.11	0.10	0.38	0.38	-0.16	-0.16	-0.05	-0.14
	[0.59]	[0.59]	[0.95]	[0.91]	[−0.75]	[−0.74]	[−0.17]	[−0.59]
Dr	-0.24	-0.26	-0.36	-0.42	-0.14	-0.13	-0.24	-0.29
	[−0.81]	[−1.01]	[−0.64]	[−0.92]	[−0.36]	[−0.35]	[−0.77]	[−1.18]
MKT		1.22		2.15		-0.00		1.49
		[0.85]		[0.98]		[−0.00]		[1.05]
const	1.09	1.00	0.61	0.37	2.01*	2.07	0.57	0.46
	[1.24]	[0.77]	[0.51]	[0.19]	[1.74]	[1.40]	[0.43]	[0.37]
MAE	0.35	0.35	0.34	0.33	0.35	0.35	0.28	0.28
R^2	48.69	48.81	57.23	57.59	42.68	42.73	60.98	63.55

Market prices of risk estimates in a linear factor model. An intercept is included in the cross-sectional regression. Test assets are 25 portfolios sorted by size and book-to-market ratio (in columns 3 and 4), 25 sorted by size and investment (in columns 5 and 6), 25 sorted by size and profitability (in columns 7 and 8), and all 75 portfolios (in columns 1 and 2). We use portfolio returns in excess of the cumulative 3-month Treasury bill rate. Mean absolute errors (MAE) and R^2s are expressed in percentage points. The primitive consumption categories are *food and beverages purchased for off-premises consumption* (Nf), *clothing and footwear* (Nc), *gasoline and other energy goods* (Ne), *other nondurable goods* (No), *Motor vehicles and parts* (Dm), *Furnishings and durable household equipment* (Df), *Recreational goods and vehicles* (Dr), *Other durable goods* (Do), and *services* (S). All results are based on quarterly data from 1963:Q3 till 2016:Q4. Details on the data are provided in Appendix A.

G Details about the textual analysis

To count energy words in firms' 10-K reports, we first download all idx files named `form.idx` from https://www.sec.gov/Archives/edgar/full-index/. These indexes list all files that were submitted to the SEC by firms. In particular, they contain the company names, Central Index Keys (CIK, a company identifier), dates when files were submitted, the form type (such as 10-C, 10-K, 10-Q, etc.), and the URL where the respective report can be downloaded. We drop all forms that are not of type 10-K. We then use a Python code that loops over all quarters and firms and proceeds as follows:

1. It downloads and opens the 10-K report.
2. It removes all tables. Tables can be identified by the HTML code at the beginning and end of tables.
3. It removes exhibits, again via the HTML code.
4. It removes remaining HTML code. For that purpose, it uses the python library "Beautiful Soup". Remaining HTML code is removed manually.
5. It removes the document header, which is identified via the table of contents or other fixed terms that show up in most 10-K reports.
6. It deletes numbers, symbols, and some words (such as months).
7. It removes stop words. For this purpose, we search for words that are listed in the "Terrier" stopword list.
8. It counts the total number of remaining words.
9. It counts the number of energy words (see Table H.1).
10. It writes the company name, the CIK, the filing date, the total number of words, and the number of energy words in a csv file.
11. It closes the 10-K report and deletes it from the hard disc.

The CIK number is available in Compustat, such that we can easily match the observations from the two data bases. We additionally check if the company names are similar.

H More comprehensive word list

Table H.1: **List of energy words**

word	freq	word	freq	word	freq	word	freq
actinide	0.000	anthracite	0.004	anthracitic	0.000	benzine	0.000
benzene	0.014	carbon	0.366	climate change	0.000	coal	0.975
crude	0.889	diesel	0.287	doe	0.016	drilling	1.883
eia	0.020	electric	1.635	electricity	0.500	electro	0.114
emissions	0.548	**energy**	4.011	engine	0.529	ferc	0.463
fissile	0.000	fossil	0.083	fracking	0.003	**fuel**	2.092
gas	8.724	gasoil	0.002	gasoline	0.303	geothermal	0.049
geothermic	0.000	gigawatt	0.003	gwh	0.006	iea	0.005
iaea	0.000	joule	0.004	kerosene	0.004	kilowatt	0.025
kwh	0.041	lng	0.161	lpg	0.053	mineral	0.386
nuclear	0.486	**oil**	5.551	opec	0.025	petrol	0.002
petroleum	0.832	plutonium	0.001	power	4.259	powered	0.122
propellant	0.013	radioactive	0.108	radioisotope	0.006	solar	0.267
tanker	0.028	tankship	0.000	terrawatt	0.000	thermal	0.295
thermoelectric	0.005	twh	0.002				

Words in the energy word dictionary that is used in the textual analysis in Section 5. Words in bold font are used to define the energy intensity measure EI. All words are used to define our alternative energy intensity measure. For each word, the table also shows the relative frequency of these words, expressed in basis points.

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