The "Average American" Unmasked: Social Structure and Differences in Household Energy Use and Carbon Emissions

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ABSTRACT

Although we routinely hear that the "average American" consumes twice as much energy as the "average European," studies of household consumption have shown considerable variation within the United States. However, policy analysis and forecasting still relies heavily on consumption averages for typical end-uses of energy, and efforts to segment consumer populations tend to look either at broad distinctions (e.g., single family vs. multi-family dwellings) or at psychological traits from small samples. Social theory and past research suggest, however, that household energy use is actually highly structured by household composition/dynamics, status-appropriate dwellings and appliances, and lifestyle-based behavior patterns. To date, relatively little attention has been given to systematically analyzing and reporting the respective effects of those factors.

We report the results of detailed household-level modeling of electricity and natural gas use in a recent sample of 1,627 Northern California households. Combining detailed survey data with billing histories of electricity and gas consumption and matched weather data, models of consumption at the household level are estimated and the social structuring of consumption is explored. Evidence of distinctive social patterns of energy use is reported. The research goes beyond prior work, to estimate total and fuel-specific carbon emissions for households (which are found to vary widely and follow closely the lines of social structure, but sometimes in surprising ways).

Problem and Research Strategy

This paper examines the highly diverse household-level patterns of energy use in northern California. While conventional energy analysis tends to focus on commonalities and population averages, we are concerned with understanding *variability* in energy use across the population. Our analysis uses utility and survey data that measure annual electricity and natural gas consumption, weather/climate conditions (locations and temperatures), dwelling characteristics (types, sizes and ages), and household demographics (income, home ownership, ethnicity, and household composition). All of these variables have been used previously in energy analysis at the household level, where they have been found to be associated (sometimes quite strongly) with one another. Our research has primarily been concerned with factors that influence electricity use, although we also present preliminary results of analyses focused on natural gas consumption and carbon dioxide emissions at the end the paper.

Variability in electricity consumption across the sample is extreme: from a few thousand kilowatt hours per year in some cases, to over thirty thousand in others. Common measures of central tendency (e.g., mean, mode and median) are misleading in this case because of a highly skewed distribution (discussed below). Two primary components of the California Energy

Commission (CEC) residential demand forecasting model—housing type (e.g., single family detached, multi-family, mobile homes) and climate zone (e.g., five zones in this sample, ranging from coastal to hot valley climates)—are found to be associated with energy demand patterns. However, their effects are sometimes not as large as might be expected, and a number of other factors not explicitly taken into account in demand modeling (e.g., dwelling size, income, ethnicity, family form) are also found to be important in explaining variations in consumption.

The use of average values—e.g., average annual electricity use, average dwelling size, average number of televisions per household—is a common and necessary practice in energy forecasting and policy analysis.[1] These averages are useful in *aggregate* estimation of trends and impacts. Given the usual limitations of available data and resources, their use is unavoidable. However, the extreme *variability* of energy consumption, particularly in the residential sector, means that these averages do not provide the detail needed to understand underlying patterns of demand or carefully target programs and policies.[2] They also do not provide information about different rates of technology adoption or levels of energy use in the population—information that is increasingly necessary to understand the dynamics of trends and to identify differential equity outcomes. Moreover, if averages are taken to mean "typical" or "widespread," this can lead to policy blind spots and ineffective interventions.[3]

The analysis reported here uses the best available household electricity and natural gas consumption data, disaggregated to the household level. When combined with detailed survey information about these same households, a series of highly disaggregated models can be estimated that consider the individual and joint effects of a variety of factors that influence consumption.

Relatively little work of this sort has been done in the past to support energy efficiency policy intervention and forecasting. Although, large data sets are routinely assembled by the Federal government, the CEC and utilities, their level of resolution and access are often limited.[4] Lacking adequate information from those sources, we were able to use data collected for other purposes in California—data of high quality, with a reasonable sample size, but lacking a total set of the variables that would be desired to fully analyze patterns of energy use at the household level. For example, we have good consumption, building, climate, and demographic information, but insufficient knowledge of appliance stocks and specific behaviors.

Key elements of the CEC residential demand forecasting model that could be used to examine these data—e.g., differences in housing type and climate—served as the starting point for the analysis. Another key element of the CEC model is appliance or technology stocks (described in detail in RASS, see CEC 2004). Unfortunately, we had very limited information about electrical end use technologies in our data. However, these technologies are, in some cases, fairly universal (e.g., refrigerators, furnaces, water heaters, televisions), or are less common but strongly associated with consumer characteristics (e.g., spa heaters, pool pumps, central air conditioners).

The analysis reported here uses a variety of socio-demographic variables—which turn out to be very powerful in our models—to capture the effects of both behavior of household

[1] Most often the arithmetic mean is used, but sometimes also median and modal values.

[2] See Lutzenhiser & Lutzenhiser (2006) for a more detailed discussion.

[3] See Stern (1986) for a discussion of "blind spots" in energy policy analysis.

[4] For example, the DOE/EIA Residential Energy Consumption Survey (RECS) and the California Residential Appliance Saturation Surveys (RASS).

members and the presence of high consumption appliances. It can be considered a form of segmentation analysis, but one in which factors other than consumer social characteristics are explicitly taken into account.

A preliminary investigation of variation in natural gas and carbon dioxide emissions is also reported.[5] As policy development accelerates around reducing fossil fuel emissions and the rate of climate change, this information can be of considerable value in targeting interventions and regulations, as well as in recognizing uneven equity impacts of alternative policies.

Relevant Literatures

The relevant literatures are found in sociology, anthropology, psychology, and economics. Only short summaries are provided here. Along with the architecture/assumptions of the CEC forecasting model, they inform variable selection in our analysis.

Following a thorough search and review of the economics literature focused on household energy use, Kriström (2006) concluded that many empirical studies have used data only from the U.S., and a majority has focused on electricity, employing a "…smorgasbord of different estimation methods, data sets and levels of aggregation…" As a consequence, the results have been quite varied, although Kriström identifies some common themes: (1) demand for energy is generally price-inelastic (although energy demand seems to respond to price over the long-run), (2) demand is associated with income (but the relationship varies substantially across studies), (3) there is no agreement across studies about the effects of age and numbers of children on energy use, (4) temperature is a key exogenous factors, and (5) to the degree that the impact of demographic variables on energy consumption can be detached from the influence of income, research suggests that energy consumption varies over the family lifecycle, between ethnic groups, and in terms of cultural practices.

In terms of the latter point, non-economic studies have considered the demographic correlates of household energy use since the 1970s e.g., Newman and Day 1975; Uusitalo 1983; for a review, see Lutzenhiser 1993). Sociologists and anthropologists have offered theoretical explanations for observed demographic differences that emphasize differences in cultural behavior patterns, social-structural conditions, consumption regimes, lifestyles, and status-ordering (e.g., Lutzenhiser 1992; Hackett & Lutzenhiser 1991; Shove et al. 1998; Schipper et al. 1989; Lutzenhiser & Gossard 2000). However, very little empirical work has been done in any of these areas over the past two decades. We can have some confidence that as persons perform everyday complexes of behavior, they are involved with other social actors, as well as with their buildings, equipment, work, lifestyles, and interactions with the natural environment. Together, these behaviors and interactions result in energy flows and emissions patterns that vary across the population. Considerable work remains to identify the precise nature of these differences and the "drivers" involved—some of which are clearly behavioral, while others implicate buildings and machines with somewhat autonomous effects. The point of the research reported here is to begin to identify significant sources of difference in energy demand in a specific population and to begin to assess the relative effects of those sources.

[5] CO_2 from the combined effects of power plant emissions and direct combustion of natural gas in the residence.

The Sample

The data set used in this study was constructed in connection with a survey of northern California natural gas customers who were facing steep increases in gas prices in early 2006.[6] Energy use data included a one-year period prior to the price increase, during which customers' usage of both gas and electricity could be assumed to be "normal"—in the sense that it took place several years after the 2001-02 California electricity supply crisis and there was no inkling that anything was likely to change in the future. The sample size was 1,627 households. Since natural gas usage is expected to be strongly influenced by weather conditions (e.g., for space heating and water heating end uses), temperature data were added for the analysis.

Past experience and the literature suggest that renters, high energy users, and very low energy users are often under-represented in residential energy surveys, simply because they are more difficult to contact, less likely to be available for interview, and/or are less willing to participate. So data from the 2000 U.S. Census Public Use Micro-Data Samples were used to estimate population characteristics at the county level and selected sample household characteristics were used for weighting to those proportions. These included: *home ownership* (own/rent), *number of persons in household*, and *dwelling type* (single family, townhouse, apartment/condo, mobile home). About 76% of sample households owned their homes (vs. 60% in the population), sample household size was 3.4 persons (vs. 2.8 in the population), and 80% of the sample lived in single-family detached dwellings (vs. 63% in the population). The use of weights brought all of these into closer alignment with population parameters. The weighting also brought the sample closer to the population in distributions of *income* and *ethnicity*, although the lowest income group and Latino/Hispanic households continue to be under-represented in the sample (although sufficient numbers participated to allow confident analysis).

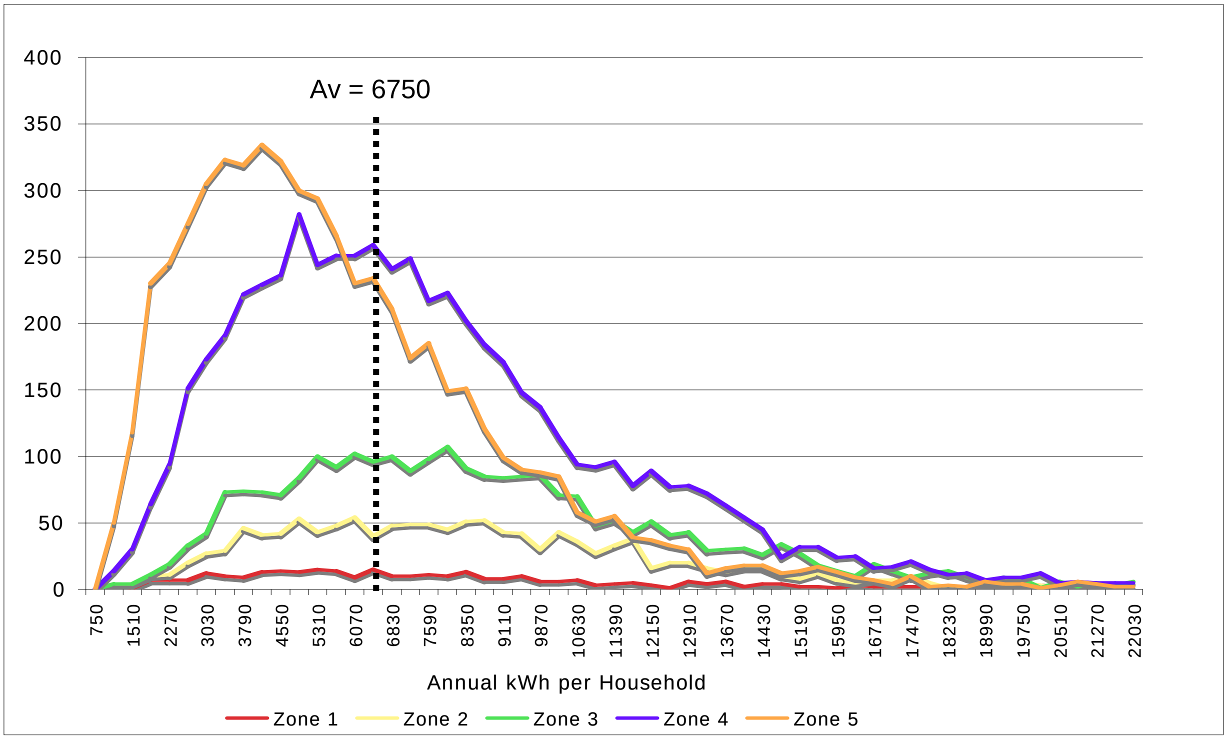
Key Variables

There are two fundamental variables in the analysis. The first is electricity consumption, measured as annual kilowatt hours (kWh). In the sample, this variable ranges from a low of a few hundred kWh to more than 30,000 kWh. The sample mean is 6,750 kWh per year. However, this is in a highly skewed distribution. The second variable is weather/temperatures to which the household is exposed. Since, even in northern California, there are seasonal extremes of hot and cold (and accompanying rain, wind and humidity conditions), the CEC has identified five *Climate Zones* in northern California.[7] When consumption averages are estimated for households living in each of these zones, we find that the mean annual kWh actually varies from 5,544 kWh (zone 5) to 8,454 kWh (zone 3). The distributions of consumption for each zone are presented in Figure 1 (also in proportion to their population size, with numbers of households on the Y axis).

[6] Because the sample comes from a natural gas study, a number of all-electric homes (i.e., accounts without natural gas) and customers that purchase their electricity from municipal utilities in the Bay Area and Sacramento are not included. The remaining cases purchase both gas and electricity from PG&E and represent about 88% that utility's residential customer base and the vast majority of all Northern California residential consumers.

[7] See a CEC forecast climate zone map at http://www.energy.ca.gov/2006publications/CEC-400-2006-005/CEC-400-2006-005.PDF.

Figure 1. Distributions of Annual Electricity Consumption Within Climate Zones



We also were able to use finer-grained measures of weather/climate conditions than those afforded only by the CEC climate zone designation—specifically heating and cooling degree days (HDD and CDD), which capture a range of differences among the five CEC forecast climate zones. And when developing the household survey instrument, we included questions that would allow us to collect information on factors that have been shown by previous research to be key influences on residential energy consumption, including:

- *Building characteristics:* Measured by building type (single family detached, multi-family, mobile home), building size (number of rooms and square footage estimated by occupants), and building age (also estimated by occupants).
- *Social characteristics:* Annual household income, home ownership (owner/renter status), self-reported ethnicity, and household composition (measured as numbers of adults [18+ yrs] and numbers of children; 31% of California households have one adult member and 47% have two adults; about one-fifth of the former and one-half of the latter also have children; the remaining 22% of California households have three or more adults, with or without children (USBC 2004)).

Relationships Among Independent Variables

The correlation matrix in Table 1 reveals a large number of associations among the causal variables and with the primary dependent variable, annual kWh. We looked closely at the relationships between the housing types and key social variables, including home ownership, ethnicity and lifecycle stage. There are notable associations between dwelling type and size, income and size, income and ownership, building size and household size and consumption. Home ownership almost exclusively involves single family detached units in the sample; Hispanics, African Americans and Asians are much more likely to live in multi-family units than are Whites; and young people, older people and singles are less likely to live in single family detached dwellings.

Table 1. Correlation Matrix: Buildings and Social Dimensions

	S Fam	Du/T/Rw	Apt/Con	Mobile	Sqft	Bldg Age	Income	Owner
Single Family	1.000	NA	NA	NA	.523**	.028	.183**	.502**
Du/Tri, Town/Row	NA	1.000	NA	NA	-.032	.030	.075*	.019
Apt or Condo	NA	NA	1.000	NA	-.474**	-.016	-.186**	-.626**
Mobile home	NA	NA	NA	1.000	-.213**	-.083*	-.144**	.133**
Bldg Sqft	.523**	-.032	-.474**	-.213**	1.000	.111**	.367**	.453**
Bldg Age	.028	.030	-.016	-.083*	.111**	1.000	.154**	.124**
Income	.183**	.075*	-.186**	-.144**	.367**	.154**	1.000	.292**
Owner	.502**	.019	-.626**	.133**	.453**	.124**	.292**	1.000
Latino	.041	-.050	.003	-.041	-.061	.025	-.162**	-.087**
White	.004	.031	-.069*	.110**	.093**	-.078*	.176**	.145**
African-American	-.037	-.018	.070*	-.043	-.042	-.006	-.159**	-.119**
Asian	-.030	.064*	.013	-.043	-.057	.109**	.018	-.022
N adults 18+	.234**	.022	-.245**	-.066*	.282**	.074*	.118**	.125**
N Kids 0-17	.111**	-.057	-.062*	-.063*	.125**	.100**	.075*	-.019
kWh	.353**	-.045	-.315**	-.128**	.416**	.170**	.296**	.308**

	Latino	White	Af-Amer	Asian	N Adults	N kids	kWh
Single Family	.041	.004	-.037	-.030	.234**	.111**	.353**
Du/Tri, Town/Row	-.050	.031	-.018	.064*	.022	-.057	-.045
Apt or Condo	.003	-.069*	.070*	.013	-.245**	-.062*	-.315**
Mobile home	-.041	.110**	-.043	-.043	-.066*	-.063*	-.128**
Bldg Sqft	-.061	.093**	-.042	-.057	.282**	.125**	.416**
Bldg Age	.025	-.078*	-.006	.109**	.074*	.100**	.170**
Income	-.162**	.176**	-.159**	.018	.118**	.075*	.296**
Owner	-.087**	.145**	-.119**	-.022	.125**	-.019	.308**
Latino	1.000	NA	NA	NA	.134**	.253**	-.039
White	NA	1.000	NA	NA	-.176**	-.243**	.015
African-American	NA	NA	1.000	NA	-.012	.035	-.008
Asian	NA	NA	NA	1.000	.172**	.082**	.017
N adults 18+	.134**	-.176**	-.012	.172**	1.000	.231**	.350**
N Kids 0-17	.253**	-.243**	.035	.082**	.231**	1.000	.250**
kWh	-.039	.015	-.008	.017	.350**	.250**	1.000

* - sig at .05 level (two tailed)

* - sig at .01 level (two tailed)

Multivariate Models

Because of the correlations among predictor variables, it is not clear from a bivariate analysis whether an effect of ownership is really caused by housing type, or whether a climate difference is at least partly due to income, or if ethnic differences reported in other research are swamped by underlying group differences in income and/or housing. In reality, the effects of these factors are joint. Weather has an effect. Housing characteristics have effects. So do the preferences and behaviors and technologies associated with the lifestyles of different social groups. But what can we say about the relative strength of these effects? Are they the same for gas and electricity? Do they vary by climate? How can they be most concisely presented?

In an effort to address these questions, we estimated a large number of ordinary least squares regressions of electricity, natural gas and carbon dioxide on combinations of causal variables. We varied the specification of the models, the coding of the variables, the order of entry, and various ways of handling missing data. We examined the models for influential cases, collinear relationships among predictors, and patterns in the residuals. We were concerned about getting the correct variables in the models. We were interested in the statistical significance of controlled relationships between predictors and the dependent variables. We also explored possible interaction effects, and compared the overall fit of various models.

The models that we present in Tables 2 and 3 are the most parsimonious and stable to have emerged from the analysis. Their relative simplicity is the result of considerable work, and their parameter estimates are quite stable with changes in specification.

Whole Territory Models

The models presented in Table 2 are for annual electricity consumption: (1) across all climate zones and (2) for zones 2-4 only. Zone 1 is quite small in terms of population, and the similarities of the two models suggest that consumption there has little effect on the overall pattern. The model that excluded zone 1 was estimated in order to provide a basis of comparison with the fully interactive four-equation model presented in Table 3.

The results show significant effects for particular climate zone locations. They also would show significant effects for cooling (but not heating) degree days if the zone variables were not included in the models. It turns out that the zone variables alone and the degree day variables alone are much poorer predictors than the two together. The zones are carrying information about more than just climate, and the CDD variable captures subtle differences within zones.

The models also show significant effects for single-family detached units (but also for multi-family units—all in comparison to mobile homes, the omitted category), for building size (but not for age), for income, home ownership, Latino and Asian ethnicities, and for numbers of adults and older children in the household. The overall fit of the model is fairly good by social science standards, with an R square of .40 (meaning that approximately 40% of the variance in the dependent variable is accounted for by the combined effects of the independent variables included in the model). The model parameter estimates can be used to compare the magnitudes of particular effects and combinations (discussed below).

Table 2. Whole Territory Models of Annual Electricity Use (kWh)

	ZONES 1-5		ZONES 2-5	
	B	Sig.	B	Sig.
CDD (100s)	-27.70	.53	-25.70	.56
HDD (100s)	-43.00	.25	-44.00	.24
Zone 2	-1,162.24	.31	ŠŠ	ŠŠ
Zone 3	-212.02	.85	943.41	.07
Zone 4	-2,592.61	.02	-1,409.97	.02
Zone 5	-3,216.19	.00	-2,037.75	.00
Single Family	2,648.55	.00	2,650.40	.00
Duplex/Tri, Town/Row	1,619.58	.04	1,625.30	.04
Apartment or Condo	1,860.78	.01	1,849.14	.01
Bldg Sqft (1000s)	642.21	.04	629.14	.04
Blt_84_96	319.29	.32	353.16	.27
Blt_97-04	308.42	.48	331.51	.45
Income ($1000s)	13.44	.00	13.56	.00
Owner	773.72	.01	767.38	.01
Latino	-1,296.16	.00	-1,283.58	.00
Af-Amer	631.40	.19	647.11	.18
Asian	-1,005.11	.07	-1,013.77	.07
N of adults 18+	857.97	.00	855.03	.00
N 13- 17 yrs	1,326.28	.00	1,327.14	.00
N 6- 12 yrs	421.94	.02	425.17	.02
N Infant - 5 yrs	16.90	.94	-32.65	.88
(Intercept)	3,384.01	.08	2238.259	.16
	R-sq = .40		R-sq = .40	

Interactive Model Differentiated by Climate Zone

Based on earlier research and our initial modeling, we believed that climate zones might differ in a fairly wide variety of ways, including housing stock, cultures, and very different temperature regimes. To test this notion, we estimated a separate equation for each of climate zones 2-5 (omitting zone 1 because of small size). This is the fully interactive model, in which it is assumed that most other variables in the equation interact with climate zone to produce different levels of effects upon the dependent variable.

Table 3 presents this combined model. It shows that the climate zones are, indeed, different from one another. Some of the significant terms in the all-zone model seem to apply mostly in certain zones and not in others. The heating and cooling degree day effects are significant only in zone 5. Building size and age are only significant in zone 5. Income effects are visible in zones 3-5. The effects of ownership are weakened but still present across several zones.

Table 3. Interactive Model: Patterns of Electricity Use Differentiated by Climate Zone

	ZONE 2		ZONE 3		ZONE 4		ZONE 5	
	B	Sig.	B	Sig.	B	Sig.	B	Sig.
CDD (100s)	288	.60	6	.98	72	.29	-169	.00
HDD (100s)	338	.57	-108	.54	47	.37	-176	.00
Single Family	6,004	.72	2,865	.06	3,233	.00	-1,164	.40
Duplex/Tri, Town/Row	11,559	.50	994	.67	1,550	.20	-1,890	.19
Apartment or Condo	6,322	.70	3,341	.04	1,440	.19	-1,756	.22
Bldg Sqft (1000s)	1,416	.41	138	.89	321	.52	891	.03
Blt_84_96	-1,516	.27	-1,182	.16	134	.79	2,054	.00
Blt_97-04	-1,019	.63	-489	.66	114	.86	663	.38
Income ($1000s)	10	.47	49	.00	16	.00	7	.01
Owner	3,256	.09	562	.51	848	.10	759	.08
Latino	1,021	.56	-1,007	.24	-985	.11	-1,461	.00
Af-Amer	5,271	.07	1,654	.28	29	.98	412	.49
Asian	53	.99	ŠŠ	ŠŠ	-900	.26	-101	.89
N of adults 18+	1,155	.03	1,423	.00	935	.00	383	.04
N 13- 17 yrs	917	.44	1,644	.00	1,153	.00	852	.01
N 6- 12 yrs	228	.89	589	.16	418	.15	-10	.97
N Infant - 5 yrs	1,214	.33	-895	.24	-110	.73	677	.05
(Intercept)	-17,705	.51	1,967	.79	-2,094	.30	8,758	.00
	R-sq = .47		R-sq = .53		R-sq = .43		R-sq = .36	
	Overall Interactive Model R-sq = .44							

Latino households consume considerably less (controlling for all other factors) in zones 4 and 5. But African Americans seem to consume more (controlling for other factors) in zone 2. And the effects of Asian ethnicity have disappeared in the interactive model. Numbers of adults is still a potent predictor, but the effects of numbers of children are less noticeable, except for teenagers in three of four zones.

For three of the four sub-models, the fit (measured by R square) is better than in the whole territory models. The fit of the overall interactive model can be estimated by comparing the total regression sum of squares with the total sum of squares for all sub-models. The overall R square value for the interactive model is a fairly impressive .44 (44% of variance explained), despite the fact that actually explaining the patterns of effect revealed in the interactive model is not straightforward (and certainly not intuitive). Our conclusion is that continued work to discover and measure differences—environmental, social and structural/technological—across climate zones can be productive.

Relative Contributions of Environment, Building and Social Variables

We were interested in estimating independent, additive effects for environmental, dwelling and socio-demographic variables in our regression analysis. We have also identified interaction effects with climate zone, the other independent variables, and the target electricity variable. But because the predictors are all correlated to some degree, it would also be useful to try to get a sense of the unique and joint contributions that environmental, dwelling and social variables make to explained variance in the model.

To do this, a series of regression models was estimated in which the different sets of predictors were entered in different orders into the equation. The explained variance (R square) at each step was compared to that of other orders of entry, allowing estimation of "unique" and "joint" explanatory powers of sets of variables. In this analysis, the unique contributions to explained variance of the social variables was 36%, building characteristics 9% and environment 17%. The remaining 39% is the result of the undifferentiable joint effects of people, environment and buildings.

The somewhat surprising finding is that the social factors—not the environment and buildings—provide the greatest amount of unique explanatory power. Also, considering that an equal amount of explained variance is attributable to joint effects (which include the social dimensions of behavior, status, etc.) social factors turn out to be by far the most potent predictors of electricity use.

Household Types and Modeled Consumption

Model coefficients can be used to estimate the annual consumption of households defined by a combination of factors considered in the model. Table 4 shows the results for nine household types that should be familiar to the reader. What is quite interesting here is the very wide—but now much more explicable—variation in total household electricity use resulting from the combination of social, environmental and building factors. The consumption levels of these households range from a modest 1,461 kWh, for a single urban lower-income adult, to over 13,000 kWh in a probably quite typical middle class suburban family. In none of these examples are the household composition, housing characteristics, or environmental conditions in any way extreme. But the different patterns of factors result in very different end-use patterns and total consumption levels that warrant much closer examination in future research.

Table 4. Model-Estimated Annual kWh for Typical Households Defined by Combinations of Environment, Building and Social Characteristics

Typical Households	**Modeled kWh per Year**
Zone 2, SF, 1200 sqft, pre 1984, $35k/yr, owner, white, 1 adult	6,376
Zone 2, SF, 3600 sqft, 1997-2004, $140k/yr, owner, white, 2 adults, 2 children	13,151
Zone 3, apt, 1200 sqft, 1984-96, $50k/yr, renter, Latino, 2 adults, 3 children	6,652
Zone 3, SF, 3200 sqft, 1997-04, $80k/yr, owner, white, 2 adults, 3 children	13,410
Zone 4, SF, 1800 sqft, 1997-04, $75k/yr, owner, white, 2 adults	7,252
Zone 4, townhouse, 1500 sqft, 1984-96, $65k/yr, owner, white, 1 adult, 1 child	5,036
Zone 5, apt, 1000 sqft, $80k/yr, renter, Asian, 2 adults, 1 child	3,223
Zone 5, SF, 1800 sqft, pre 1984, $100k/yr, owner, white, 2 adults	6,613
Zone 5, apt, 800 sqft, pre 1984, $20k/yr, renter, Asian, 1 adult	1,461

Modeled Annual Household Natural Gas Usage, Carbon Dioxide Emissions and Total Consumption in Btus

Table 5 shows the results of regression analyses of natural gas consumption, carbon dioxide (CO_2) emissions, and combined electricity and gas energy use expressed in British thermal units (Btus). The same predictors are used as in the electricity analysis above. The fit of the models is not quite as good for natural gas and Btus as for electricity and CO_2.

Hot weather (CDD) has significant (but negative) effects in several models, as does single family detached structure, and building size. Vintage of building is only significant in the natural gas model, where units built in the late 1980s-early 1990s used less energy than older and newer units. Income effects are strong across models. Ownership effects are weaker. Controlling for other factors, Latino households produce significantly less carbon, while African Americans may produce more. Factors such as housing quality and equipment efficiency that are not included in the model, but are possibly correlated with ethnicity, may play a role here. Numbers of adults and older children affect CO_2 emissions, but not natural gas consumption or overall Btu levels.

Table 5. Models of Natural Gas, Carbon Dioxide (CO2) and Total Btus

	Therms Natural Gas (100k Btus)		Pounds Carbon Dioxide (CO_2)		Total Btus (1000s)	
	B	**sig.**	**B**	**sig.**	**B**	**sig.**
CDD (100s)	-12	.00	-155	.01	-1,289	.00
HDD (100s)	-4	.20	-73	.13	-523	.00
Zone 2	-111	.21	-2,071	.16	-15,100	.14
Zone 3	-74	.40	-987	.49	-8,102	.16
Zone 4	-205	.02	-4,130	.01	-29,380	.44
Zone 5	-157	.08	-4,004	.01	-26,630	.01
Single Family	70	.18	2,628	.00	16,060	.01
Duplex/Tri, Town/Row	14	.82	1,280	.20	6,952	.01
Apartment or Condo	-120	.03	-88	.92	-5,682	.34
Bldg Sqft (1000s)	82	.00	1,383	.00	10,439	.40
Blt_84_96	-54	.03	-400	.33	-4,351	.00
Blt_97-04	-40	.25	-241	.67	-2,931	.15
Income ($1000s)	0	.00	15	.00	95	.48
Owner	23	.36	792	.05	4,907	.00
Latino	-9	.74	-997	.02	-5,323	.10
Af-Amer	143	.00	2,067	.00	16,461	.10
Asian	-21	.63	-931	.19	-5,511	.00
N of adults 18+	-1	.91	579	.00	2,815	.29
N 13- 17 yrs	14	.37	1,079	.00	5,966	.02
N 6- 12 yrs	4	.78	336	.14	1,836	.00
N Infant - 5 yrs	21	.21	256	.36	2,205	.27
(Intercept)	641	.00	9,647	.00	75,691	.28
	R-sq = .25		R-sq = .37		R-sq = .33	

This first cut at modeling CO_2, in particular, is a promising start at informing climate policy with more rigorous understandings of how the variability in consumption of multiple forms of energy produce variegated patterns of household carbon emissions.

Conclusions

The analysis shows that residential energy use and carbon emissions are highly variable in the population of interest. A large proportion of the observed variation can be explained by a relatively small set of variables, including: climate zone/temperature, dwelling type and size, building age, home ownership, household income, ethnicity, and household composition. This is true for both electricity and natural gas consumption, as well for CO_2 emissions.

The relationships between forms of consumption and the independent/predictor variables are not simple, however. Many of these variables have significant correlations with other predictors (e.g., income and dwelling size, household composition and building type, even income and climate zone). These correlations do not violate the assumptions of the models used, but they make interpretation of results somewhat challenging. Also, there are unmeasured factors that influence consumption and emissions levels that could not be considered in this analysis. These include appliance characteristics, building condition, household behavior, and more subtle weather variations, to name a few.

The fit of the various models that we estimated were fairly good, and we conclude that the approach is promising. Household consumption is neither merely "average" nor idiosyncratic or otherwise random. Residential energy use and CO_2 emissions are structured—by past decisions about dwelling form and technology, current patterns of occupancy and behavior, and changing climate/temperature conditions.

Although we cannot apply the specific findings with confidence beyond the population of combined gas and electric customers in northern California, possibly similar/possibly different patterning is certain other contexts.

Future Research Needs

More complex models can be estimated, and more complete data can be obtained to further develop our understanding of the structuring of household energy consumption and emissions. Further analyses should:

- Explore in greater detail the social, environmental and structural/technological differences among climate zones that seem influential in determining differences in energy use patterns.
- Use other data to apply this approach, but in an expanded form in which appliance stocks are explicitly taken into account (in the current analysis, they are subsumed in the environment, building and socio-demographic terms).
- Develop suggestions for a more refined set of questions that might be included in future data collection in order to develop a richer base of information for forecasting, policy analysis and program planning.
- Explore the policy implications of the social patterning of demand for: simulation modeling and forecasting; the development of rates, regulations and subsidies; and program design and implementation (e.g., targeting specific social groups and patterns of usage).

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