Lifestyles, Buildings and Technologies: What Matters Most?

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ABSTRACT

There is considerable variation across households in energy use, even within similar climates and housing styles. There is also considerable variation in energy savings following upgrades of housing and appliances. We combine empirical data on household consumption with advanced simulation modeling techniques to investigate just how much behavior matters in determining consumption levels—compared to weather, technology and building characteristics. We explore several new concepts, including the BETA (building, environment, technology, activity) Model of household energy use, a *habitation zone* approach that can be used to differentiate BETA effects, and a hybrid (simulation/ statistical) end-use consumption analysis approach. For illustrative purposes, we report the consumption dynamics within three representative dwelling types, located in four different California climate zones, and occupied by a range of households. We also consider energy saving potentials from building retrofits and appliance replacement under different occupancy/activity conditions. We conclude with a discussion of the implications for energy efficiency policies and programs of our findings that behavior may determine up to 2/3 of typical home energy use, or more depending on heating and cooling requirements and environmental conditions.

Introduction

In this paper, we investigate the sources of energy use in the residential sector and their contributions to variation in energy use across households. Our fundamental question is "How much do each of the most likely factors—building characteristics, weather, energy-using devices, and consumer behaviors—influence natural gas and electricity demands in homes?" A related policy question relevant to next-generation energy efficiency programs is "How can we design home efficiency upgrades to optimize the interactions among these factors?"

These questions are not new, and we are not attempting to reinvent decades of analysis focused on energy savings potentials and efficiency program design and impacts. A good deal is known about various energy end-uses, and a number of conventional policy instruments—ranging from demand forecasting systems to building simulation models, deemed savings databases, and consumer education initiatives—commonly rely upon estimates of "typical" energy demands for various residential energy uses. There would seem to be an established base of common knowledge.

However, we also find a good deal of uncertainty about that knowledge. Some energy end-uses such as lighting may be fairly well understood as a result of past systematic study (e.g., KEMA 2010a, 2011). Others we know in principle to be small (e.g., bedside clocks or rarely used small kitchen appliances). But some major end-uses such as home heating and cooling are highly dynamic, vary considerably across the population and have yet to be understood in much depth. The household use of hot water is also poorly understood. So too is a large "miscellaneous" category of plugged-in devices or "plug loads."[1]

It is not surprising that our understandings of major components of household natural gas and electricity use are limited. Most of the research these past two decades has ignored the behavioral aspects of home energy use. Though significant effort has sought to understand the quality of building shells and appliances, this has been found insufficient to explain current, and predict future energy use. Most of the program interventions have focused on improving the efficiency of building shells and appliances.[2]

In this paper, we build upon, but go beyond, existing knowledge of residential energy use to explore the relationships among the primary sources of demand at the household level. As an early part of a larger research agenda, we limit our current analysis to the investigation of two specific topics: (1) the relative sizes of different sources of demand (the "BETA factors" discussed below) within a single geography, in this case the state of California, and (2) how the sizes of efficiency savings potentials from major home upgrades vary and are influenced (amplified or dampened) by those demand elements—particularly household activity or occupant behavior. The BETA model results highlight the importance of incorporating behavior in energy and climate change policy discussions and program designs. With the appropriate research on behavior, models like BETA will be better able to guide policy orientations and programmatic activities to reduce residential energy use and/or greenhouse gas emissions.

Background: A Basis in Theory

The home as an energy-using system has been the focus of research for several decades. The factors that seem to affect demand levels should be fairly obvious by now. It is clear that with normal construction practices more energy is required to maintain comfortable indoor temperatures in both cold and hot climates than in mild ones —therefore, we see higher average residential energy use in New York and Texas, than in California or Florida (EIA 2009). Architectural factors (e.g., dwelling size, shape, materials, quality of construction, insulation levels, glazing, and mechanical systems) have been noted by building scientists and energy efficiency analysts to all make a difference in energy use. As a result, building characteristics have been frequent targets for building code upgrades, design innovations, technology standards, and definition of industry 'best practices' that take energy performance explicitly into account. Another set of factors is found in the relative energy efficiency of appliances, home electronics, lighting, and other "plug loads." These are typically regulated via Federal and state minimum energy performance standards to reduce waste in these end-uses. Finally, human activity has been widely recognized as playing a major part in household energy consumption. How people interact with, control and otherwise *use* building systems, appliances and plugged-in devices, has a powerful influence on total energy demand in homes.[3] But how do these factors relate?

[1] Plug loads are an estimated 11% of aggregate California residential electricity demand (KEMA 2010b).

[2] For discussions of variability, see Lutzenhiser and Bender 2008. Readily available sources of residential demand and household data include the U.S. DOE Residential Energy Consumption Survey (EIA 2009) and the California Residential Appliance Saturation Survey (RASS) (KEMA 2010b).

[3] For example, long-recognized large consumption differences among households in identical neighboring dwellings (Socolow 1978) and large differences in demand estimates in statistical models after controlling for weather and building differences (Lutzenhiser and Bender 2008).

It has long been recognized that these environmental, architectural, technological, and behavioral elements are linked together in a complex system—one that requires an *integrated theoretical model* to understand its dynamics and the possibilities for intervention.[4] But despite repeated calls for such a model, it has yet to be fully developed. We have been working toward that goal as part of our Advanced Residential Energy and Behavior Analysis (AREBA) project sponsored by the California Energy Commission (CEC).

Policy Importance of Better Understanding Residential Consumption

A better understanding of residential consumption is useful because it allows improved forecasting, building codes, technology standards, and efficiency programs. Current models used in these areas emphasize parts of the residential consumption system while downplaying others that may be of critical importance in understanding and influencing changes in energy use. For example, in *demand forecasting*, which is used to make official predictions of energy demands within housing stocks and climate zones, weather and technology are emphasized, with less attention to building characteristics and virtually none to variation in user behavior. State *building codes* and *technology standards* govern the energy requirements of new residential construction and common household equipment (e.g., electronics, air conditioners, refrigerators, etc.). In supporting analyses, human activity is either taken to be "typical" or un-addressable. Finally, in energy *program interventions,* retrospective impact evaluations quantitatively estimate energy savings from specific equipment upgrades, while averaging out the effects of weather and user influences. In each of these policy areas, estimating the sizes of consumption by end-use is of central concern, and together they have spawned a supportive array of data collection and analysis activities and tools. However, in every case we could benefit from improved knowledge of end-use patterns, which would improve our forecasts of demand and our ability to shape future energy use.

Limits of Conventional Statistical Approaches

Actual measurement of consumption for various end-uses has been costly, complicated and, therefore, rare. Creative use of statistical estimation is a common substitute that combines information from utility bills and customer surveys. For example, *conditional demand analysis* (CDA) uses regression modeling to predict energy use relative to weather measures such as Heating Degree Days (HDDs) and Cooling Degree Days (CDDs). CDA includes variables for kinds of equipment in each household—for example, the seasonal energy efficiency rating (SEER) of the air conditioning unit, dummy variables for particular appliances present, and potentially the energy using and saving behaviors in the household (e.g., line drying clothes rather than using an electric dryer, although, in practice, behavioral estimates are almost never made). The data are then pooled so that the regression coefficients associated with the equipment variables indicate the average effect of included end-uses on monthly bills.

Unfortunately, the CDA approach suffers from the twin problems of *multi-collinearity* and *missing variables.* In the former, associations between particular end-use variables result in over- and under-estimation of the effects of correlated variables. In the latter, the effects of unmeasured behaviors and equipment are erroneously attributed to variables in the explanatory

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[4] See Keirstead (2006) for a review of the history of integrated residential consumption models and an assessment of lack of progress in improving those models.

equation. As a result, CDA-based estimates of consumption for specific end-use devices (e.g., central air conditioners, clothes dryers, gas furnaces, pool pumps, and other appliances and systems) vary considerably across samples and years (e.g., RASS 2003 vs. RASS 2009), without apparent cause (KEMA 2009, 2010b). One obvious solution to these problems is much better measurement, which, as noted, has been impractical or prohibitively expensive (KEMA 2009). The result of this lack of measurement is substantial uncertainty about the respective sizes of important end-use energy demands and of potential energy savings from major building and equipment upgrades.

In the balance of this paper we use existing sources of data on residential consumption in California and our compact BETA model of demand to systematically explore the range of magnitudes and relationships among energy end-uses. Our intention is to demonstrate that a clearer overall picture of residential demand is possible, within the limits of currently available data. After describing our methodology and research design, we report our findings and conclude by discussing implications for policy and energy saving programs, as well as needed research for the future.

Analysis using the BETA Model

Because of the limitations of CDA and lack of data from which alternative statistics might be estimated, we chose a hybrid modeling approach that explicitly takes into account the four key factors in the residential consumption system (buildings, environments, technologies, and human activities). We call this our "BETA Model," which can be expressed formally as:

$$\textit{Energy Demand} = f(\textit{Building, Environment, Technology, Activity})$$

Our methodology combines (1) existing information on consumption ranges for certain end-uses (e.g., hot water heating, lighting, appliances and plug loads) with (2) simulation modeling of building physics and heating, ventilating and air conditioning (HVAC) loads. Building simulation was deemed necessary and appropriate since parsing out amounts of energy used for household heating and cooling when aggregated with other end-uses is tricky, at best, using statistical techniques. Both heating and cooling demands are closely (but not necessarily linearly) related to weather, which is usually not measured at the site of each home. HVAC loads are also related to a variety of ordinarily unmeasured building characteristics, as well as to unrecorded household behavior involved in the management of buildings and HVAC systems.

In *building energy performance* studies, architects and engineers routinely use simulation models to test designs of new buildings and assess the performance of existing buildings for optimizing energy efficiency. Unlike simple statistical estimation of HVAC energy use, state-of-the-art simulation models can take into account a host of simultaneous interactions between weather conditions, building designs, materials, HVAC system designs and efficiencies, air exchanges, solar effects, and so on. They are able to model minute-by-minute thermal conditions and energy requirements of buildings within very complex, changing environmental conditions. While such models are not designed for precise prediction of consumption in existing buildings, their grounding in building physics offers a possibility of better isolating thermal loads that are more uncertain in statistical analyses.

We know that occupant activity—human behavior—plays a large role in the real-world building thermal performance and energy demands that we would simulate. Since the earliest studies of large variations in the energy use of nearly identical buildings (Socolow 1978), building scientists have recognized these *occupancy effects* and within the last decade have begun to investigate various dimensions of occupancy using advanced building simulation modeling techniques (e.g., Azar 2010; Clevenger and Haymaker 2006; Robinson et al. 2011). We were able to build upon this work with our own simulations, exploring the simultaneous effects of building design, HVAC systems, weather, and occupant activity on heating and cooling energy demands.

To analyze non-HVAC energy demands, we were able to identify a number of existing studies of California residential energy use, as well as several publically available data sets from which we were able to extract our own information about consumption patterns and demand distributions. A few studies have used actual end-use measurement (e.g., of lighting or hot water), while others have at least collected occupants' self-reports about household equipment holdings and thermostat control patterns, sometimes combined with utility measures of monthly electricity and natural gas consumption (e.g., KEMA2010b). We offer caveats about the accuracy of self-reported information about appliance stocks and household behavior, but note that these sorts of data are all that are available and are routinely used and trusted in CDA and other analyses that support the California policy activities discussed above.

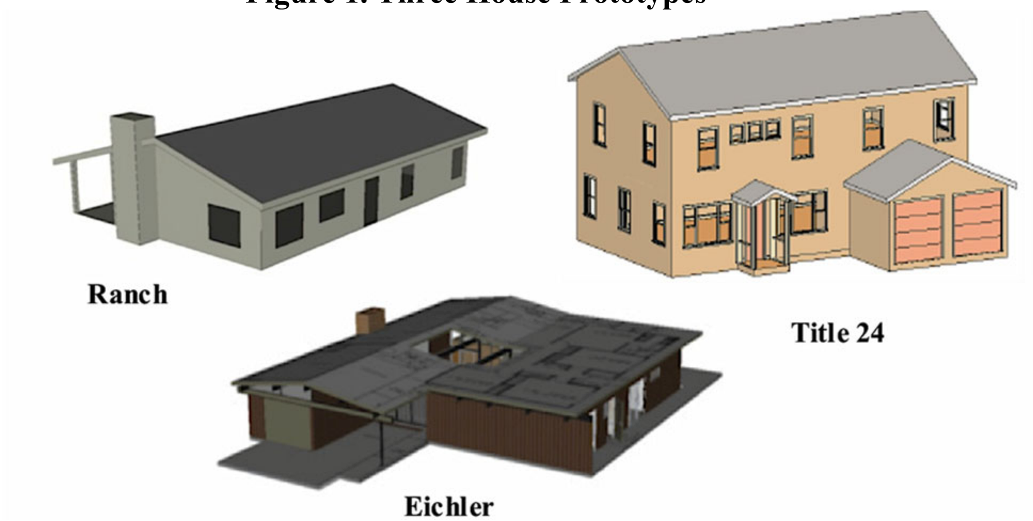
In our analysis, we were able to combine simulated HVAC demands and non-HVAC loads to estimate the relative sizes of BETA factors in household energy demand, and to investigate how lifestyles and major efficiency upgrade effects may interact to increase or decrease overall consumption, within different building styles and environments. As noted, our findings are provisional and represent the early stages of work in this area. However, we believe that they illustrate some important dimensions of residential demand and raise some useful questions for further study.

Research Design

The fundamental starting point of the analysis is the home as a context for human activity. So we began by characterizing the dwelling(s). We then situated those buildings in different climate conditions, populated them with household(s) and technologies, simulated thermal performance and HVAC energy use, added in non-HVAC electricity and natural gas consumption, and analyzed relative effects. The simulation environment was provided by the U.S. Department of Energy's energy performance modeling system *EnergyPlus 7.0* (DOE 2012). Because we were interested in investigating the simultaneous interactions of a large number of causal factors (described below), a large number of simulation runs were required (approximately 9500 in all), using *jEplus* (Zhang 2009), a dedicated parametric analysis tool, to interact with *EnergyPlus*.

Step One: Characterizing buildings. We selected three single-family styles for our analysis. The first style is a quite common California "ranch" house built from the 1960s to the 1980s. It is an "average" exemplar of average size and uncomplicated design. The second prototype is an "Eichler style" (named for the original builder), a common "California modern" design built during the 1950s and 1960s with low rooflines, lots of (single-glazed) windows, and sometimes even open atrium spaces in the middle of the house. The third prototype is an "official" modeling prototype developed as part of the California Title 24 Energy Code process, used for testing and certifying building performance modeling software packages for Title 24 compliance. Images of the three houses are shown in Figure 1.[5]

Figure 1. Three House Prototypes



The Ranch was selected in part because it is intrinsically "upgradeable" through addition of attic insulation (not possible in the Eichler design and not necessary in the Title 24 prototype). Both the Ranch and the Eichler can benefit from air sealing and improved furnace efficiency retrofits (the Title 24 building was assumed to already have minimal air leakage and a high-efficiency furnace). Also, the Ranch could also benefit from an air conditioner upgrade (the Eichler has no air conditioning and the Title 24 unit is assumed to have a high-efficiency AC). Table 1 summarizes key differences among the three tested prototypes.

Table 1. House Prototype Characteristics (Model Input Parameters)

Model	Vintage	Size (sqft)	Wall Insulation	Ceiling Insulation	Leakage Area	Heating Efficiency (AFUE)	Cooling Efficiency (SEER)
Eichler	1964	1660	R-10	R-7	220 sq in	70%	no AC
Ranch	1972	1664	R-10	R-10	220 sq in	75%	6
Title 24	2008	2700	R-13 * R-19 **	R-30 * R-38 **	140 sq in	95%	13

* California Climate Zones 4,7,10 (South Bay, San Diego, Riverside) ** California Climate Zone 13 (Fresno)

A detailed model of each house design was constructed, including shell dimensions, materials, insulation, windows, leakage area, furnace efficiency, AC efficiency, internal heat loads from refrigerator, home electronics (major plug loads), lighting, and human occupants.

[5] While these three prototypes certainly do not represent all of the California houses built since the 1960s, approximately 70% of the current housing stock was constructed over that period (U.S. Census 2012) and many of those units share energy-relevant features with our prototypes.

Other site-specific and occupant-specific factors influencing building performance were held constant in the modeling.[6]

Step Two: Environmental conditions. The California Energy Commission identifies 16 distinct climate zones for purposes of Title 24 energy efficiency code compliance. However, for our analysis we selected four zones with extremes of weather (a policy-relevant factor) and large population concentrations. Our techniques could be used in any climate conditions. The four zones are the Central Valley (Fresno), with extremes of both heat and cold, shown by the Heating Degree Day (HDD) and Cooling Degree Day (CDD) values in Table 2. They also include temperate coastal climates (San Diego), warmer inland Los Angeles basin areas (Riverside) and the somewhat protected (from the summer chill) areas of South San Francisco Bay (Sunnyvale).

Our *EnergyPlus* runs simulated thermal/energy performance for a one-year period, using CEC annual weather data files for these four Title 24-designated areas (CEC 2012). *EnergyPlus* used information from the files on daily high and low temperatures, humidity, wind speed, and solar radiation.

Table 2. Test Climate Heating and Cooling Comparisons[7]
(CEC Title 24 Modeling Year)

Climate Zone	HDD 65	CDD 65
Fresno	2,335	1,926
San Diego	1,429	468
Riverside	1,794	1,266
South Bay	2,512	281

Step Three: Technology stocks Household technologies influence energy use in several ways. When they are present, their usage provides various services and experiences to residents, with resulting energy demands and increased household consumption levels. In terms of the BETA model, the "T" term (technology) only has effect to the degree that technologies are in place and are actually used.[8]

In our analysis, we specified the presence of a large number of devices, systems and appliances. But we varied the efficiency levels of some (e.g., furnaces, air conditioners, refrigerators) and varied the usage levels of all of the devices listed on Table 3.

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[6] These include orientation, shading, occupant use of window coverings, and opening/closing of windows. These factors can potentially have significant effects on building thermal performance and space conditioning energy demands. Ignoring them likely biases upward simulated heating and cooling loads.

[7] HDD 65 and CDD 65 measures are conventionally reported U.S. Weather Service statistics. As measures of the difference between the average daily temperature (here the mid-range temperature of daily high and low temperature, as defined by NOAA) from a base of 65°F, they are widely recognized as imperfect. However, they are readily available and commonly used in energy analysis and forecasting.

[8] Although technology has been *the prime focus* of efficiency efforts for decades, the devices per se consume no energy (other than standby losses) and are inextricably bound up in their energy use with the actions of *their users*.

Table 3. End-Use Technologies Considered in the Analysis

Devices Modeled in the Simulation	Devices Modeled Alongside the Simulation
Forced air furnace (with electric blower)	Hot water heater
Air Conditioner	Dishwasher, Gas Range/Oven
Refrigerator	Kitchen appliances
Home electronics and computer equipment	Clothes Washer and Dryer
Lighting	Vampire plug loads

Equipment types with associated heat loads (e.g., refrigerators, home electronics and computer equipment, lighting) were included in the thermal modeling. Other devices without (or with less certain) heat load contributions, were considered alongside of the model and combined with the thermal/HVAC modeling results later in the analysis. Our consumption estimates were not simply fabricated, but obtained from studies and data we examined. Also, we did not use *point estimates*, but specified a series of *usage distributions* from low to high consumption levels to reflect the variability of energy use across the population. Data sources included RECS and RASS surveys (EIA 2009; KEMA 2004, 2010b), studies of lighting (Gaffney et al. 2011; KEMA 2010a), home electronics and plug loads (Brown et al. 2007; Porter et al. 2006), hot water usage (GTI 2012), and published information on appliance efficiencies (e.g., EERE 2012).

Step Four: Activity types and levels. Occupant activity has only recently come to be considered more than a tangential element in building simulation—unlike transportation modeling, for example, where activity-based simulation is becoming the norm. For our analysis, a primary dimension of "occupancy" is whether people are actually present in the house.

Table 4. Activity Schedules and Temperature Preferences

Work Outside of home				
Heating	**Morning**	**Day**	**Evening**	**Night**
1	55	55	66	55
2	60	60	68	60
3	68	62	68	62
Cooling				
4	off	off	off	off
5	off	off	72	off
6	78	78	72	78
Lighting (% on)	10	0	40	5
Someone Home During the Day				
Heating	**Morning**	**Day**	**Evening**	**Night**
7	60	65	65	60
8	68	68	68	68
9	70	70	70	63
10	73	73	73	73
Cooling				
11	80	80	76	76
12	78	78	78	78
13	72	72	72	72
Lighting (% on)	20	10	40	5

We were able to introduce occupant activity levels in the modeling by drawing upon self-reports of thermostat management and reasonable assumptions about patterns of presence and control from data on workforce participation and lifecycle demographics of the population. Examining the available data (e.g., RASS), we find a number of different temperature setting patterns, some with extreme levels of heating and/or cooling. Table 4 shows some illustrative schedules selected to investigate the effects on demand of a range of what we judged to be both fairly common and "reasonable" (at least recognizable) activity/control schedules.[9]

Results

Having specified the BETA factors, we performed the following analyses: (1) examination of the performance of different building types in different environments, (2) construction of a *habitation zone baseline* to compare the respective sizes of BETA elements, and (3) estimation of efficiency improvement potentials (and differences) and comparison of their benefits across different lifestyle categories.

Buildings and Environments

The building itself does little without people manipulating it. However, it does enclose and "shelter" a space of potential habitation, and can do this with greater and less success, depending on the environment and its own attributes (how well it gains heat from the sun, how well it holds the heat when outside temperatures fall, how "leaky" it is when the wind blows). Different building designs should perform quite differently in different environmental contexts. To test this, we simulated our prototypes over the course of a typical meteorological year (TMY) in a "free running" state—unoccupied without any HVAC equipment or utility-supplied energy available. As we might expect, the Title 24 design was better at maintaining warmer temperatures in winter and somewhat cooler temperatures in the summer in this simulation. Not surprisingly, all of the designs maintained relatively pleasant temperatures many days of the year—a testament to California's generally mild climate in comparison to much of the rest of the United States.

Of course, part of the time indoor conditions were more extreme for all of the designs. The results led us to wonder how much energy might be required in different locales if these same buildings were heated and cooled minimally, using the same types of HVAC equipment, leakage levels, etc. A "minimum" level of heat and cold that may be tolerable for any kind of human habitation can be set at a variety of levels, of course. People around the world are surviving (in some cases quite satisfactorily) at temperature extremes that someone attuned to a 68 degree Fahrenheit room might find intolerable. For our analysis, we defined the *habitation zone baseline* by setting the minimum tolerable indoor temperature (the set-point at which a high-efficiency furnace would turn on) at a very cool 55 degrees, and we set the maximum temperature (the set-point to start a high-efficiency air conditioner) at 90 degrees. Again, debates can be had about these particular set-points, but the principle is valid and the findings are useful, as we shall see.

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[9] For Title 24 energy code compliance purposes, model heating and cooling schedules have been specified (CEC 2008). However, they do not include heating and cooling controls set to "off," which are fairly common in self-report data. So we selected several patterns using the "off" option. Although we do not include the Title 24 schedules in Table 4, they are similar to schedules 8 and 12.

Performing these tests and comparing results (reported in Table 5), led us to realize that the Title 24 dwelling (the most efficient by design), when located in the most temperate climate (San Diego) with the smallest heating and cooling requirements, required very little purchased energy to maintain these minimum habitation conditions. In fact, only 37 annual kilowatt hours (kWh) of energy was required by that building, despite its much larger size. In the real world, with active human management of the building envelope, even less energy would likely be required to heat and cool that large building to higher comfort standards—even given that the building was not designed to be particularly conducive to passive heating and cooling strategies. Active management strategies were not tested at this stage of the research.

Table 5. Simulated Energy Requirements with Minimal Heating and Cooling

House Prototype and Location	Annual Electricity (kWh)	Annual Natural Gas (therms)	Annual Total Electricity + Gas (MJ)[10]	Annual Total per 100 sq ft (MJ)
Eichler				
Fresno	3,431	62	18,871	1,137
Riverside	1,999	12	8,482	511
San Diego	463	1	1,784	108
South Bay	758	42	7,112	428
Ranch				
Fresno	2,987	51	16,140	971
Riverside	1,464	5	5,824	349
San Diego	229	0	827	50
South Bay	417	30	4,612	277
Title 24				
Fresno	2,228	45	12,745	471
Riverside	867	1	3,201	119
San Diego	37	0	133	4
South Bay	118	20	2,554	94

Other prototypes fared less well in San Diego, of course, and when all of the dwellings were "moved" to less temperate climates, their energy demands—just to maintain these minimal indoor conditions—increase considerably, to a high of 18,871 MJ in Fresno for the Eichler model and even 12,745 MJ for the building built to current Title 24 standards in Fresno.

Estimating BETA Effects

What is particularly useful about this approach is that it allows us to make comparisons of relative effects—i.e., to estimate the respective sizes of the different BETA contributions to overall energy use. The results of our analysis are shown in Table 6. Our building performance baseline is the state-of-the-art Title 24 house situated in San Diego. By comparing the total modeled demand of the other prototypes to the Title 24 design, we can calculate the size of the design effects of each prototype compared to the Title 24 case. By comparing the total demand of the Title 24 design in each of the other three climate zones with the Title 24 San Diego

[10] Combined electricity and natural gas energy expressed in Megajoules (MJ), which is the primary *EnergyPlus* output unit of end use energy. Conversion factors: 1 MJ = 0.278 kWh, 1 MJ = 0.00948 therms.

minimal baseline, we can estimate an environmental effect that is assigned to all of the prototypes.

This lays the groundwork for an analysis of the effects of occupancy and activity, which was also a multi-stage process. It is necessary to acknowledge again that our "T" (technology) term is impossible to differentiate as a contributor to demand on its own and independent of human activity and control. However, with *efficiency upgrades* (considered below), changes in T can be important contributors to energy *reduction*. In the building and environmental effects analysis, both technology and activity were intentionally excluded. They were introduced into the analysis via the 9500 *EnergyPlus* model runs that varied a range of activity and technology parameters for each housing type and climate zone. These inputs included HVAC control set-points and schedules, lighting schedules, equipment efficiencies, building leakage rates, heat loads from appliances and people, and thermal contributions of a set of energy uses involving refrigeration and home electronics.[11] Again, the model runs covered a range of both low occupancy patterns and high occupancy patterns. They also included low and high appliance usage and lighting, as well as lower efficiency HVAC, leakage and insulation, along with retrofit runs that improved the efficiency of all of these.

Table 6. Estimating BETA Factor Proportions

	Total Demand (MJ/yr)	Building Design Effect (%)	Climate/ Weather Effect (%)	HVAC Activity Effect (%)	Other Activity Effect (%)
Eichler Fresno	97,378	6	13	32	49
Riverside	80,924	7	4	31	58
San Diego	73,697	2	0	34	64
South Bay	92,642	5	3	41	51
Ranch Fresno	130,852	3	10	52	36
Riverside	111,405	2	3	52	42
San Diego	94,672	1	0	49	50
South Bay	110,492	2	2	53	43
Title 24 Fresno	105,984	0	12	43	45
Riverside	91,260	0	3	45	52
San Diego	80,963	0	0	42	58
South Bay	94,380	0	3	47	50

By determining the ranges of all runs for each housing type and climate zone combination, we were able to gauge the extremes in demand for each prototype. Estimates of energy use for non-modeled appliances and devices (e.g., hot water heating, cooking, laundry, home electronics, etc.) were then brought into the analysis alongside of the thermal/HVAC modeling results. Selecting the mid point value in the ranges for both activity/behaviorally driven HVAC and additional forms of energy use (plug loads, appliances, hot water, etc. combined), we were able to construct a reasonable estimate of total demand to use in our BETA parsing analysis

[11] The other end-uses identified on Table 3 were not in the modeling at this stage.

(reported in Table 6).[12] Comparing the resulting modeled values to the corresponding California RASS results for 2009, we find our estimates of total demand to be within about 10%—not a "validation" of our results, but an indication that we are not dramatically off target.[13]

The general patterns of the results shown suggest that, all BETA factors play a role with some being much more pronounced than others depending on the situation. One striking finding is the overwhelming effect of occupancy/activity/behavior in the use of technology, compared to the other two major factors. It seems obvious that living in a place that's not too hot or cool will minimize potential environmental effects on demands for HVAC. It's also clear that some designs fare better in some environments than in others. In all cases, what people "do" with their houses and equipment makes an enormous difference in how much energy is consumed. Residential demand is the result of an *activity/behaviorally driven system.* The BETA Model results demonstrate this convincingly.

Building and Technology Upgrades

Does this mean that improvements to buildings and systems are irrelevant? Not at all. Building shell upgrades and technology codes and standards are practices and policies that do provide savings. But our analysis suggests that the benefits depend considerably on the activity patterns of building occupants.

For this analysis, we selected for testing several upgrades/retrofits that are important policy and program targets. These include shell performance (air sealing and insulation) and HVAC upgrades. We modeled the effects of cutting air leakage approximately in half, increasing attic insulation in the Ranch model, increasing furnace efficiency in the Ranch and Eichler, and increasing AC efficiency significantly in the Ranch model. Assuming that occupant heating and cooling demands would make a difference in the impacts of upgrades, we also tested the improvements under a range of occupant schedules. For the analysis, each measure was installed in the following order: (1) air sealing, then (2) insulation, then (3) furnace replacement, and finally (4) AC replacement. Therefore, at each stage, the savings from the previous upgrades were taken into account (i.e., we did not "double count" potential savings). Results for the Ranch house in Fresno for heating only are shown in Table 7.

Table 7. Energy Savings for Ranch House Upgrades

Heating, Cooling, Water Heating, Appliances and Plug Loads	Annual Natural Gas Demand (MJ)	Savings from Air Sealing + Insulation + Furnace (MJ)	Savings as % of Annual Natural Gas Demand	Saving as % of Annual Total Energy Demand
Low demand	5,696	– 3,586	63%	10%
Medium demand	27,954	– 13,924	50%	9%
High demand	49,051	– 19,831	40%	9%

[12] The additional non-HVAC energy uses ranged from about 20,000 to 75,000 MJ/year, with 47,318 representing a moderate average usage level.

[13] Direct comparisons are not possible, since RASS reports only a recent year's aggregated demand, while our simulations use a synthetic "typical meteorological year" constructed from weather data for a number of past years.

We found that the savings can be substantial, although varying a good deal with heating and cooling demand by residents. Persons with lower heating and cooling requirements save a good deal less than those who heat and cool more. As this case illustrates, estimated cumulative savings ranged from a low of 3,500 MJ for those who use little heat to more than four times that amount for those with higher indoor temperature levels. The savings as a percent of total natural gas use varied from a high of 63% to a low of 40%. Both are very respectable numbers, but as a proportion of overall total annual household energy use, a more modest 9-10% reduction was estimated. As expected, we also found significantly lower savings from these upgrades for all households in more temperate climates, and for single measure upgrades (e.g., air sealing or insulation or furnace replacement only). To the question “How much can major residential energy retrofits yield?” we can respond “It depends to a very large degree on behavior.”

Conclusions

Our research has shown that it is possible to differentiate sources of residential energy consumption by using advanced building simulation techniques in combination with the results of previous empirical field studies. The precision of our approach can certainly be improved, and we are in the process of refining our tools and databases. To date, we have found that we can successfully parse the BETA factors using house prototype and climate zone comparisons, with both building design and weather playing smaller parts that might have been expected and occupant activity proving to be a dominant factor. We also found that retrofits and upgrades should certainly be able to deliver significant energy efficiency benefits, but strongly shaped by the lifestyles and usage patterns of occupants’ heating and cooling practices.

What are the implications for policy? For one thing, the “Other Activity” (non-HVAC) effect is surprisingly large—as much as 1/3 to 2/3 of total household energy use. When combined with the HVAC-related activity effects, the “A” factor in the BETA model overwhelms all of the others, with the environmental and building design factors accounting for only 1%–20% of total household demand, depending on structure and location.

Clearly occupant activity (“behavior”)—what people are doing—demands serious policy attention and programs need to better appreciate the importance of these “human elements” of energy use. In practical terms, this means that the wide *variation in end-use demands* strongly suggests that “one size fits all” is likely not a recipe for policy and program effectiveness or equity. Also, the benefits of major building retrofits and equipment upgrades seem to be highly variable across the population, which homeowners may already know but needs to be explicitly taken into account in program design and delivery. Possibly large energy saving retrofit investments would be warranted for some households, especially large consumers of air conditioning and heating. However, for others who have low occupancy levels and/or otherwise lower cooling and heating demands, the same investments would provide much smaller benefits. In the end, the wide array of sometimes small energy uses in typical households can add up to very large demand levels that dwarf the potential savings from even major building, system and appliance retrofits. Highly efficient major systems do not guarantee low energy usage, and behaviors, both “good” and “bad,” matter a great deal.

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