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Determinants of Residential Heating and Cooling Energy Consumption

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Household energy demand can be seen as a derived combination of discrete and continuous choices on the part of the consumer. Consumers make initial discrete decisions when purchasing the durable appliances which use energy to heat and cool homes. The frequency that the appliances are later used at is a continuous decision made by the household. Different types of HVAC equipment yield different efficiencies in their consumption of energy, so the type of equipment selected and the demand for energy are endogenously linked. However, the HVAC market is prone to inefficiency, as consumers do not demand energy, but rather a comfortable and welcoming climate in which to live. A house can be kept climatised regardless of the efficiency level of energy use, so it is not difficult for consumers to either neglect or not be aware of an inefficient or excessive consumption of energy. This means that energy efficient initiatives like weatherization or sustainable housing can be neglected. This research attempts to contribute to the study of residential energy consumption for heating and cooling by analyzing the composition of factors which contribute to household energy demand. Using microdata from the United States Energy Information Administration's 2009 Residential Energy Consumption Survey, our empirical model conducts a technical dissection of energy use across five climate regions. From this, conclusions can be drawn as to what drives energy demand in the five different climate regions in the United States. This will have implications for formulating cost-effective public policy which would help address excesses and inefficiencies in residential HVAC energy consumption.

I. MOTIVATION

The magnitude and impact of residential heating and cooling energy consumption is significant. Household climatisation is by far the most expensive system for a given household, accounting for an average of 54% of total yearly energy consumption by end use. Moreover, it is not only expensive, but also a source of carbon emissions, be they from the house itself or from the power supplier. Fortunately, HVAC technology has improved dramatically over the past half century, and architectural techniques have developed which maximize the efficiency of residential energy use. Holistic approaches to design, such as the whole-house approach, have been credited in some cases with creating houses which generate as much energy as they consume. These advances have made it so that newly constructed homes use on average 40% less energy per square foot than those built before 1950. However, modern homes are substantially larger, a development which has worked against these gains in efficiency.[1] Furthermore, many residencies continue to rely on outdated HVAC equipment, and houses continue to be built in climates which demand higher levels of energy use. Others have noticed this, and there has been growth in environmental consciousness as people have become more aware of the environmental impacts of excessive energy use. Well-meaning people take pride in changing their behaviors to be more environmentally friendly. They use eco-friendly compact fluorescent light bulbs, unplug non-critical appliances, and opt for Energy Star qualified appliances. But these slight adjustments do little to offset the structural trend of modern American houses. Even those wishing to do good for the environment more often than not do so in a structurally unsustainable house. How much control do people have over their energy

[1] Figure 1 shows the trend towards larger houses over time.

consumption? How much are they locked into their demand? These questions are significant, and in order to adequately address them, it is important that we know what drives energy demand on a household level. Of course our physical constraints are chosen by different initial decisions, but things like where we have built housing, how large we have built it – these are all decisions that would be very costly to change. However, their exploration is worthwhile. While it may be expensive to change the existing housing stock and its location, information on their relative effects on energy demand is important to know for making informed decisions for future growth. Additionally, it allows for more nuanced policy. New or altered government policies may be appropriate if it turns out that the current social costs do in fact outweigh the private costs.

II. LITERATURE

One way to examine the cost of switching heating and cooling technologies is to examine the discount rates of investment in efficient appliances. Although more efficient technologies tend be priced higher, they reduce the marginal cost of heating and cooling a home. Many studies on heating and cooling technologies argue that heating technologies, and to a lesser extent cooling technologies, have higher discount rates than real interest rates, which could make them viable investments for households (Ruderman, 1987). One important assumption, however, is that maintenance costs for energy efficient and inefficient technologies is the same (Ruderman, 1987). If these discount rates are accurate, some of which for heating are near 100%, investing in these new technologies could be paid back within a year of the investment (Ruderman, 1987). Potential barriers to investment then would most likely be the high upfront costs of switching to new technologies or a lack of information on the part of the consumer (Ruderman, 1987). Policy implications could be subsidized loans on energy efficient heating and cooling technologies and outreach programs on changing technologies and weatherizing homes. In fact, many engineering based studies estimate that 20-60% of household energy use could be eliminated at a negative cost considering the discount rates of various household appliances (Greenstone, 2012).

However, other studies argue that these discount rates are based on engineering studies and are not experimental and observation based. (Greenstone, 2012). These studies probably have omitted variable bias which could bias the amount of potential savings for households on energy efficient technologies in an upward direction. For example, these studies generally group unknown, but important variables into a control group. These variables include factors such as climate and behavioral energy use. Weatherization has also been heralded as an extremely cost efficient way to reduce energy in heating and cooling, but its benefits calculations have not fully considered non-monetary costs (Greenstone, 2012). Consumers may be unwilling to weatherize their homes because of the time and inconvenience costs due to weatherization taking multiple visits from contractors and some degree of paperwork (Greenstone, 2012). Depending on a consumer's personal situation, this inconvenience may cost them more than the savings that would result from weatherization.

Energy reductions from efficiency may also be overestimated when one does not consider how changing the relative price of heating or cooling one's home will affect demand (Greenstone, 2012). In economics this is called a rebound effect, meaning people may demand more heating and cooling in their homes as efficiency increases, offsetting some of the total energy reductions from the efficiency (Greenstone, 2012). Split incentives can also result in a shortage of energy efficient technology. These split incentives fall into two categories and affect renters (Kennigan, 2010). The first category is when landlords make the decisions about how much to weatherize a home, and the renter must pay for the increased costs of energy due to inefficiencies. The second is when the landlord pays for the heating and cooling and the renter has no incentive to ration their use (Kennigan, 2010). A study in California estimates that these split incentive inefficiencies only contribute approximately 1/100th of a percent to CO_2 emissions in California, but suggest it could be higher in other states as California has strict insulation building code requirements and also moderate weather (Kennigan, 2010). Another problem in California is that electricity is priced on a per tier basis with households incrementally paying more for electricity the more total electricity they demand. In general, states may have different local energy policy initiatives, which when not accounted for on a national basis are an exogenous variable. However, in the case of California, the effects of this particular tier based policy are probably small as many households may be unaware of what tier they are on or simply find the potential cost savings in their electricity bills not salient (Kennigan, 2010). This is in line with the inherent nature of heating and cooling. Because consumers enjoy indirect utility from their fuel sources, accurately addressing efficiency requires that specific attention be paid to a residential HVAC system.

A problem with previous studies done on household behavior related to energy is that they do not tend to use panel data or experimental observation. This problem also applies to our own dataset. Panel data would better account for unobserved heterogeneity for temperature preferences (Kennigan, 2010) as well as give insight into the formulation of the discrete choices made when selecting equipment based on future expectations. Additionally, a problem with the data is that many variables that affect energy use for heating and cooling are correlated. For example, people with higher incomes are more likely to live in single detached homes (which without the walls of others are less insulated) and are more likely to have larger homes (Kennigan, 2010). Perhaps some of these physical differences are compensated by household behavior, as some have suggested that people living in colder climates are more likely to adjust their thermostats frequently, turning it down when they have less need for it (Kennigan, 2010). The extent that climate impacts energy demand is addressed in detail in our regression model.

A breadth of econometric analysis is available which focuses on addressing market effects on energy demand and predicting consumer behavior. The link between space heating equipment and energy demand was first addressed in detail by Dubin and McFadden (1984) using 1975 residential data from Washington State. They apply Roy's Identity, a method of deriving the demand function of a good from its indirect utility function, to the consumer market for energy appliances and electricity. The resulting model is a simultaneous combination of discrete and continuous choice models. They conclude that such analyses, without the use of instrumental variables, have a severe tendency for bias. Nesbakken (2012) expands on the work of Dubin and McFadden by including more detailed household characteristics like climate, size, and fuel type into her analysis of Norwegian residential data. She too finds the choice of equipment type and magnitude of usage to be endogenously linked. These studies use heating and cooling degree days in their regressions. Degree days serve as an indication of climate. The heating or cooling degree day measure of an area is calculated by taking the integral of the function of temperature over a set period of time with respect to a base temperature. For simplicity's sake, our regression model handles climate in regard to the more intuitive labeled climate area. Both Dubin and McFadden (1984) and Nesbakken (2012) conclude that much remains to determined regarding the precipitating factors of upgrading or replacing durable HVAC appliances.

Although these analyses attempt to predict and model consumer choice and market conditions, this assessment focuses primarily on deconstructing the contributing factors of net residential energy demand for heating and cooling. Previous studies worked with limited microdata, and were unable to assess the effect that physical housing attributes had on their derived energy demand models. In Dubin and McFadden's (1984), unknown and omitted household characteristics like climate, size, and appliances used are grouped into a single random vector. The Energy Information Administration dataset used here is robust in its coverage of residence characteristics, which allows for a more technical dissection of household energy demand. As a result, we are able to include detailed household weatherization characteristics in our deconstruction of energy demand. The regression model used estimates the impact of the explanatory variables as a percent of household demand for energy, rather than their contribution to total quantity demanded. The topic of interest is the relative impact of different household factors. The tools of market analysis used in other such analyses, such as marginal per unit cost of fuel, price and income elasticities, and utility functions are exogenous to our dependent variable, and are beyond the scope of the regression analysis. Our data and research can contribute to the study of residential energy consumption for heating and cooling by looking at what factors are most important in determining how much energy a household uses. There is already a volume of research on this subject, some of which use previous iterations of our dataset. Ideally, to see how important technology is in driving residential energy consumption, experimental data would be used as it is hard to account for the correlation between size of the home, income, including its effect on the ability to pay for efficient technologies, and household behavior for rationing heating and cooling in the home.

III. HYPOTHESIS

We expect to find that the data would suggest current trends in the housing market are towards less energy efficient households on a per household basis. It is anticipated that climate will play a major role in determining household heating and cooling energy consumption, with more moderate climates enjoying more energy efficiency than those located in cold, hot, or humid environments. However, homes in different climates have different architectural styles and were developed during different time periods. Because homes in certain climates may have many physical differences we do not observe such as thickness of glass, and because variables may interact differently under different climate environments, we believe that the United States' regional climates are sufficiently different that energy demand functions for them are best estimated separately. Controlling for climate, behavioral characteristics will most likely have the potential to contribute to a small reduction in energy demand, and tendencies towards certain environmentally friendly activity may serve as a proxy for general concern about the environment. Factors that are subject to some structural adjustment, like adequate insulation, up to date equipment, and general weatherization level will be more significant. This should be correlated with income level, a higher income level indicating a better weatherized house. Older homes are expected to contribute to less efficient energy use on a per foot basis, as well as be correlated with older equipment. Based on the findings of Kennigan (2010), households will most likely be more energy efficient when they are owned by the primary occupier, with the issue of split incentives contributing to the discrepancy. However, the aligning of incentives may be offset if owners tend to occupy larger sized homes. In general, it is expected that the general trend in the United States housing market is towards larger houses, with no particular propensity for houses to be built in less energy demanding climates or AIA zones. Because of this, the main conclusion that we expect to draw from our econometric analysis is that the inefficiencies and excesses in household energy consumption are inherent to structural factors which are generally out of the hands of the members of the household once an initial decision where to locate is made. This may include factors like square footage, climate location, and type of residence. This would imply that the best method of reducing household HVAC energy consumption would be through a reshaping of public policy towards one which encourages more energy efficiency during the construction of new houses and encourages smaller sized homes. As for the houses that still exist, weatherization may have merit, but will likely have a limited impact.

IV. DATA

The microdata used in our regression is from the 2009 United States Energy Information Administration's Residential Energy Consumption Survey (RECS). The 2009 version is the 13th iteration of RECS, and contains data collected in 2009 from a sample of 12,083 household units. The households are selected to statistically represent the United States' 113.6 million primary residence housing units. The households selected cover four census regions, nine census divisions, and 16 states. All primary residences in the United States are eligible for inclusion in the RECS sample. Data is collected through Computer Assisted Personal Interview (CAPI) methodology conducted by specially trained interviewers. The data collected covers energy statistics relating to the household as well as usage and demographic data. Data is gathered from the household representative as well as from the energy companies which supply RECS households. All told, the 2009 RECS microdata includes 869 data points for each household surveyed. RECS is used by the EIA to estimate national economic indicators, so measures are taken to ensure that the data be of the highest quality. RECS data goes through an intensive editing process prior to publication, and all data are validated during quality control. Missing or inconsistent data is imputed or excised, respectively. The square footage measurement included in RECS data refers to the entire heated or cooled floor space of a dwelling, which may include the garage and the attic. Additionally, RECS includes classification of households based on their Climate as well as AIA Zone. A household's climate is determined by its geographical location within the United States[2]. AIA Zone refers to one of five climatically different areas, developed by the EIA's Energy Consumption Division and based off of categories originally identified by the American Institute of Architects (AIA). A household's AIA Zone is determined according to the thirty year average (1951-1980) of annual heating and cooling degree days, using 65 degrees Fahrenheit as the base measurement. These Climate Zones correlate strongly with the climates classification of the households, so this model uses the more approachable climate designations as its primary factor.[3] Several of the variables have been altered or divided in their use in our regression. These changes will be explained in detail during the overview of our empirical model. Although the data is extensive, verified, and of high quality, there are still several imperfections with it which may lead to some measurement errors.

RECS survey microdata is cross-sectional, covering a different selection of US households in each iteration. Cross-sectional data is telling, but is unable to address some of the more nuanced factors which are better addressed through panel data. This includes heterogeneity in household preference. Although Nesbakken (2012) concluded that the only household characteristic subject to change over time was household size, panel data would still give

[2] See Figure 2 for division of climate types.

[3] Figure 3 shows the correlation between climate and AIA Zone.

excellent insight into the nature of the discrete decisions household make, such as investments in weatherization, heating equipment, and how they are influenced by their expectations for the future. Additionally, the behavioral data included in RECS is subject to some skepticism, as it is all self-reported by the household representative. Respondents may have a tendency to misrepresent themselves, over reporting their environmental consciousness or energy usage habits. Additionally, no one is robotic enough to report the true values of their actions, so some inconsistency is certainly attributable to human error in response. Unfortunately, several of the data points in RECS demonstrate significant response bias. For example, the variable INSTCFL, which asked if the household installed energy efficient compact fluorescent lamps instead of traditional incandescent bulbs, failed to get a response from nearly half of the respondents. This would be a very good indicator for energy conscious behavior, but the presence of such significant response bias reduces the validity of this measure.

In the survey we are using there is some behavioral data, but we have chosen to focus on constraints in the physical environment. A person's physical environment is the result of a choice - they choose to move there, so there is likely endogeneity. However, there are large costs to moving, so we can assume that for many people once they have moved to a location, they are locked in as to the choices of their physical environment.

RECS has a wealth of statistical data, but lacks market conditions for the household's surveyed. This means that there is some difficulty in estimating the marginal cost of energy to the household, as well as how that cost compares to other, substitutable energy sources. In our model, this is not necessary, but the model in this paper could be used to assess other issues, like energy price elasticity, some of which take into account the marginal cost of energy faced by the consumer. Additionally, the question remains whether price differentials between local energy markets are actually salient to consumers (Kennigan, 2010). A minor increase in marginal cost may simply be not significant enough for the consumer to bother changing consumption habits. It would also be interesting to see the effect on the implication on the price elasticity of energy when it is applied for different purposes, such as water heating.

Although there are flaws with the data set used, a true, or 'ideal', data set would be impossible to produce. The ideal data set would have the true measure for one's environmental concern modifier. As it stands now, current RECS data suffers from potential omitted variable bias. Environmentally conscious individuals may be more likely to live in an energy efficient residence; this would affect their overall behavior, which could cause endogeneity. Because environmental consciousness must be determined a posteriori, there is no way to know its true value. Additionally, we would ideally want to randomly assign individuals with different environmental characteristics, personal preferences for temperature, and other unobserved personal characteristics to different types of housing with different equipment, size, and climate to observe the relative effects. However, this is unrealistic and probably unethical.

In order to produce more economically significant results, we have made several alterations to the presentation and composition of data. With square footage, extreme outliers which were more than four standard deviations away from the mean were dropped. We also dropped rare and eccentric dwelling characteristics that were atypical of reality. This included uninsulated houses, those where the occupiers neither owned nor paid rent (i.e. squatted), and those with wood as the primary source of heat. Building age has been defined as the decade during which it was built. In response to the significant impact that a household's climate has on its HVAC energy demand, we have divided the dataset into five groups based on the RECS regional climate division[4].

V. EMPIRICAL MODEL

A. Description of the Models

In total we applied four different models to estimate household energy consumption. Our dependent variable throughout all of the models was the log of total British Thermal Units (BTUs). By taking the log as our dependent variable, we measure the effects of energy consumption as a percentage change in BTUs of the household. British Thermal Units are a standardized unit of energy which measures the amount of energy required to heat one pound of water by a single degree Fahrenheit at standard atmospheric pressure (RECS). By expressing our dependent variable in BTU's we allow for households to substitute various fuel sources to meet their energy needs. We have elected to measure the percentage change in the total BTU's of households as our sample average across all climate types of total BTU's for households is over 80,000 and we believe measuring their percentage change allows for more meaningful interpretation. We have also separated our dependent variable into the five different climate categories because we believe that the categories are sufficiently different that this is warranted. Different regions of the United States vary in architectural styles, housing markets, and demographics which we are not observing in our regression. By separating our dependent variable into five different regressions we do not have to consider these unobserved variables as it will not bias our climate variable as it would if we were to include climate as a dependent variable in a single regression. Instead, these unobserved differences across climates will show up in each of our individual climate regressions' error terms. However this also makes external interpretations between the climate regions difficult, if for example square footage interacts with other important omitted variables differently across climate types.

B. First Model

Our first model attempts to describe the variation in energy consumption across households by examining personal characteristics of the household. It can be stated as follows:

(1) PercentChangeinEnergyConsumptionbyClimate = *CONSTANT* + *INCOME* + *OWNERSHIP STATUS* + *EDUCATION*

C. Second Model

Our second model controls for the variation in the size of the households. Size is measured in total square feet of the household. We log this variable so that we may interpret its coefficients as the effect of a percent change in household size on the percent change in energy consumption. This is a log-log model. The model can be stated as follows:

(2) PercentChangeinEnergyConsumptionbyClimate = *CONSTANT* + *INCOME* + *OWNERSHIP STATUS* + *PERCENT CHANGE IN SQUARE FEET*

[4] Summary statistics for the five data groups can be found in Table 7.

D. Third Model

In our third model we consider the physical characteristics of a household which affects its efficiency. These variables include the HVAC system, level of insulation, age of the home by decade which we use as an overall proxy for the trend of increasing efficiency in how homes are built due to innovations in architecture and other unobserved variables[5]. Our new model can be specified as follows:

(3) PercentChangeinEnergyConsumptionbyClimate = *CONSTANT + INCOME + OWNERSHIP STATUS + PERCENT CHANGE IN SQUARE FEET + HEATING METHOD + COOLING METHOD + INSULATION + AGE OF HOUSE*

E. *Fourth and Final Model*

Lastly, our final model additionally considers the effect of consumer behavior on total energy consumption. As mentioned previously one major endogenous variable for our regression is unobserved household characteristics that determine what types of homes households locate in and also what types of consumer behavior they exhibit, such as limiting their use of lighting and other behaviors. For example, environmentally conscious households may more likely locate in energy efficient homes, in a particular climate, and of a particular size, but also ration their energy consumption behavior in various ways. In our final regression, we attempt to use a rough proxy to estimate the household's concern for the environment. Our proxy is the respondents' answer to the question concerning whether they unplug electronics from the wall when they are not in use. Electronics when plugged into a circuit use some amount of electricity, even if the device is not in use, therefore this is an omitted variable which affects our dependent variable and should be included in initial regression anyway. However, we believe that the total effect of this one particular behavioral pattern on total energy consumption in and of itself is probably small. However, households that unplug their electronics are demonstrating concern for their energy use which is probably correlated with other types of energy rationing behaviors: such as using florescent light bulbs, turning down the thermostat when away from home, and utilizing natural sunlight when possible instead of artificial light. In aggregate, we would like to know what the effects of such behavior are on total energy consumption holding personal characteristics of the household and physical characteristics of the home constant. Our model can thus be specified as:

(4) PercentChangeinEnergyConsumptionbyClimate = *CONSTANT + INCOME + OWNERSHIP STATUS + PERCENT CHANGE IN SQUARE FEET + HEATING METHOD + COOLING METHOD + INSULATION + AGE OF HOUSE + PROXY FOR ENVIRONMENTAL CONCERN*

We find overall, the effects of this proxy statistically insignificant in most climate groups.

VI. EMPIRICAL RESULTS

In this section we will examine the effects our regressors of interest had on our dependent variable, the percentage change in energy consumption of a household measured in BTUs. The effects differ across climate types in both statistical significance and in magnitude (and

[5] See Table 6 for a description of the new variables of interest.

occasionally even in the direction of the effect). Whether these differences have real world applications or are a result of bias from omitted variables that are relevant in one climate type, but irrelevant in another is ambiguous. We believe that many of the differences in coefficients across climate types have interpretable significance, however a word of caution is warranted as each climate regression may not be entirely externally valid and able to be applied to another. For example, there may be little variation in the cooling equipment of one region, and much variation in another, leading to significance in the climate with variation, and insignificance in the other.

We also should be aware of the internal validity of each independent climate regression. Comparing climate types could be haphazard if one climate regression is internally valid, but the other is not. This could happen even using the same model across climate types because omitted variables may be important in one climate and not important in another, which would affect the different climates' error terms separately. One example which could confound our study is the importance of local state energy policies. If a climate group is primarily composed of states that have different energy policies than states in other climate groups then this omitted variable could bias the coefficients of one climate and not the others. Because the one climate group's internal validity would be compromised it should not be compared to the other climate groups. With this said, let us look at each regressor and compare it between various models and climate groups interpreting its significance as best we can.

A. Renter Status

As can be seen in the appendix, using our first model which only considers demographic information, renter status has a very large effect on energy consumption. In the cold climate type, according to the first model, renters use approximately 44% less energy than owners[6]. The difference in the hot humid climate is less pronounced, but still very significant, 35%. However, once square footage and type of home is controlled for this magnitude of the renter status quickly dissipates in every climate group. Intuitively, this makes sense. Renters typically live in smaller sized homes, which require less energy to heat and cool. This, important omitted variable heavily biased our renter dummy variable downward. The downwardly biased effect is also likely compounded by the type of home renters tend to occupy, that is apartments. Because apartments share walls with other households they use less energy on heating and cooling than detached homes which do not receive any warmth or cooling effects from adjacent households.

Once we control for the different physical characteristics of the homes renters occupy, like our literature review suggests, renters use more energy than owners. Our literature review explains this is due to an issue of split incentives. Renters often do not pay for many types of their energy consumption; it is included as a fixed amount in their rent. Thus, they do not have an incentive to ration their energy consumption. If they do pay for their own energy consumption, then landlords do not have an incentive to properly insulate the home. However, because we have included insulation in our second and subsequent models, we control for this type of split incentive. In the hot humid climate it appears that, controlling for physical characteristics, renters use 6-7% more energy than owners due to this lack of a rationing incentive. The cold climate is an exception, however. Its coefficient remained negative even after controlling for physical characteristics. Perhaps, there is still an omitted variable we are not

[6]See Tables 1-5 for detailed regression output

considering which is significant in the cold climate, but not elsewhere. If this were the case than the renter status variable would remain biased in the cold climate.

B. Income Group

Like renter status, prior to controlling for physical differences in homes across households, income group was quite significant. In general the trend for income groups, for all climate types, is the higher the income group, the higher the energy consumption. Once physical characteristics are controlled for however, a change in income is only statistically significant for high income groups (the exception is the hot humid climate at which income group is significant for every level of income). For example, in the cold climate households that fall into the income group of $100,000+ use 14.6% more energy than households below $20,000. An important variable not included in our regression is electronic appliances. The income group variable may be capturing variance in energy consumption due to this omitted variable. Likely, higher income households possess more electronics which consume more electricity. A household's energy bill also may just be less salient information for high income households. Once a household reaches a certain income level they may not concern themselves with their energy bill and thus not ration their use of energy. It is interesting that income seems to be the most significant in the hot humid climate. Perhaps, air conditioning is one of the most important activities that households ration when they are concerned about the cost of their energy bill. If this is the case it makes sense that lower income households, more concerned about their energy bill, would have the largest impact in the climate likely to demand air conditioning the most.

C. Education

Like our other demographic variables, the effect of education decreases once physical characteristics of the home such as size are considered. In fact, once these characteristics are controlled for the educational attainment level is statistically insignificant in the cold climate. However, it remains significant in both the hot humid and hot dry climates for when a household obtains a college degree or higher. Looking at the appendix, one can see that in the hot humid climate households which have a college degree or higher use 11% less energy than households which did not finish high school. One way of interpreting this result is that perhaps in college people become concerned with climate change and decide to change their behavior due to this concern. If climate change is taught earlier in cold climates than in hot climates, there would be less change in households' awareness of climate change over time and thus this variable would not show up as significant in the colder climate. The cold climate also had different results for the renter status variable, so it is possible that perhaps the cold climate is just somehow considerably different in ways that we are not observing from the hotter climates.

D. Size

Square footage was our only continuous variable in any of our regressions. We logged this variable so that a percentage change in it can be interpreted as a corresponding percentage change in total energy consumption. Across all climate types it was very significant, though not as significant as it once was without controlling for the different types of homes i.e. apartments or single detached dwellings. In the hot humid climate the coefficient for the log of the total square feet was 0.43 in our final regression model. This can be interpreted as meaning when the size of a home increases by 10% in this climate; we expect total energy consumption for the household to increase by 4.3% all else equal. This was a larger coefficient than in the cold climate whose coefficient was 0.281. Another interesting finding was that as we added more regressors such as the HVAC equipment, the magnitude of the coefficient for the home size increased somewhat for the hot humid climate and decreased somewhat for the cold climate, which contributed some to their overall divergence by climate. Perhaps square footage is more important in hotter climates because it takes more energy to cool large spaces than it does to heat large spaces.

E. Home Type

Home type is the second variable we included to control for the physical differences in homes for our second regression. In general, omitting mobile homes, (which were not statistically significant in any climate – probably because there were few observations) single-detached homes used the most energy in every climate. Intuitively, this is as we would expect. Single detached homes share no walls with other homes so these types of households receive no positive heating or cooling externality from adjacent households utilizing energy to heat or cool their own homes. In the hot humid climate, where the effects of home type were very significant, single-attached homes use approximately 22% less energy than single-detached homes, apartments in small apartment complexes (with four apartments or fewer) use 37% less energy, and apartments in big apartment complexes use 47% less energy. Economies of scale seem to be a factor here, with the more households residing in the same building in general creating less individual demand per household for energy.

F. Heating Equipment Used

Beginning in our third model, we begin to consider the relative efficiencies of the heating equipment used as well as other variables such as cooling equipment, insulation, and year built which also affect efficiency. Heating equipment can fall into many categories. In total counting households that responded “not applicable” to primary heating equipment used, there are 12 categories in our regression. The diversity of options complicates accessing which method is the most efficient in particular climate types. The question is also complicated by the fact that some households may employ an auxiliary heating method to supplement the primary heating method which we observe in our regression. This issue of omitted variable bias of auxiliary heating methods threatens the internal validity of our regressions, especially in interpreting the coefficients of the primary heating methods. For example, it may be the case that one particular heating method seems to use little energy relative to other methods, but if households universally find it to be inadequate to provide all of the heating they demand, then we do not observe their demand for an auxiliary heating method, which biases the seeming effectiveness of the primary heating method. Additionally, the heating equipment may interact with characteristics such as size of the home. Certain types of primary heating equipment such as the portable kerosene heating equipment may appear to be relatively efficient (in the cold climate they are measured as using approximately 43% less energy than the households that use a central furnace) however a portable kerosene heater likely does not have the capacity to heat the entirety of a large home. We should probably be suspicious of homes that list this type of heating equipment, typically designed to heat small spaces, as their primary heating source. These are likely unusual homes.

However, in general across all climate types we find steam to be the most energy costly option for households. In the cold climate, households that use steam heating equipment use approximately 14% more energy than households that use a central furnace. It also appears that heating equipment which use electricity, both the built-in electric and the portable electric heater, are among the least energy using types of equipment. However, as RECs cautions on their website, electricity, unlike these other fuels, is a secondary fuel which means that a primary fuel like coal must be used to generate electricity at a power plant, which is then transmitted to households. Thus, if one is interested in the raw amount of energy being used by households, electricity is biased downwards since much energy is lost during the transmission of electricity to the household from the original potential energy of the fuel source used to make electricity offsite at the power plant. Calculating this type of energy consumption is outside the scope of our study, though it may be a more effective way to measure an individual household's effect on the environment due to their energy demand. One more important thing to note is, as we would expect, heating equipment used is the most significant in the cold climate where the demand for heat is likely the highest.

G. Cooling Equipment Used

For the cooling equipment used variable, our different climate types had interesting results. In the cold climate, the type of cooling equipment used was statistically insignificant for every category. Why we should not be surprised that it would be relatively less important than in hotter climates that have greater demand for cooling, we were surprised however to see it statistically insignificant. After all, some of the heating methods were statistically significant in the hot climates. However, though the cold climate did not have statistically significant results for the cooling equipment, the trend in its coefficients was the same as the other climate groups. Households that use a window unit for air conditioning use more energy than households that use central air, and households which employ both methods in conjunction with one another use the most.

The most surprising result however, is that none of the cooling methods were statistically significant for the hot humid climate either. This is the climate which we would expect the cooling method used to have the greatest effect as we anticipate this climate to have the greatest demand for cooling. However, we suspect that this is largely in part due to the small variation in the type of cooling equipment used in the hot humid climate. Of the 2115 observations for the hot humid climate, only 334 households responded that they did not have central air conditioning. Because almost all homes in the hot humid climate have central air conditioning our sample does not observe much difference in the types of cooling equipment used and thus it is difficult for us to conclude any significance about the relative efficiency for cooling equipment in this climate.

The different cooling equipment methods were only significant in the mixed humid climate. We believe that this is because the mixed humid climate has more demand for cooling than the colder and marine climates, but also has some variation in the methods used, unlike in the hot humid climate. Of the 3,365 households in the mixed humid climate, 929 do not have central air conditioning and 665 households have window air conditioning units as their primary means of cooling their home. For this climate, households that use window air conditioners, use approximately 7% more energy than households that use central air conditioners. For the few households that use both methods together (only 65 households) they use approximately 16% more energy than households that use only central air conditioning. While intuitively it makes sense that households which employ both methods will use the most energy, we should be careful drawing conclusions about this method since only about 2% of respondents responded as employing that method.

H. *Insulation*

The level of insulation had the greatest impact in the cold climate with households reporting adequate insulation using approximately 6.5% less energy than households reporting poor insulation and households reporting well insulated homes using an additional 5% less than adequately insulated homes.

Insulation was not statistically significant in the hot humid or marine climate types. Because the marine climate type is temperate, perhaps insulation is not significant due to low heating and cooling demand in this region. The hot humid climate is more interesting. Do these results suggest that insulation is more important for heating purposes than cooling purposes? The hot dry climate had statistically significant coefficients, but the coefficients were smaller in magnitude than in the cold climate, so perhaps there is still some truth to this statement. Still, it seems like that there should be some effect, especially since there is a relatively large amount of variation in reported insulation in the hot humid climate. One problem is that we likely are not measuring the true variation in insulation across households. Our insulation data is self-reported which could cause measurement errors since households may not be that aware of their insulation level. Furthermore, households were only given four options in reporting the data (and we dropped households that reported no insulation as we think these are atypical homes). Thus, there is much less variation in our data than the variance of insulation which probably exists in the real world. Perhaps if our data was more precise there would be a negative trend in energy use with increased insulation in the hot humid climate, like we would expect and like there is most of the other climates.

I. Age of the Home (In Decades)

In general the trend for age was that newer homes decreased energy use across all climate types. There were some exceptions to this. For example in the cold climate, homes built in the 1990's use more energy than they did in the 1980's, but by the 2000's energy use was back on a downward trend. We believe exceptions such as this are likely due to curiosities in the housing market. Perhaps some feature like high ceilings was in high demand during the 1990's that caused homes to be relatively less energy efficient.

The magnitude was the highest in the hot humid climate. Here homes built in the 2000's use approximately 23% less energy than homes built before 1950. This effect is when we control for house size, however. Because homes have been increasing in size over-time some of these increases in overall efficiency are likely counteracted.

J. Unplugging Electronic Devices

The final variable we examine in our last regression is whether households unplug electronics devices such as cellphones chargers when they are not in use. As mentioned previously in our empirical model section, this behavior we expect to directly decrease total energy use in a very small amount. However, we are interested in using it as a rough proxy for other behavioral patterns that ration energy such as turning down thermostats when not home. We expect that households which unplug electronic chargers from walls likely exhibit other rationing behaviors which in aggregate could have significant effects.

However, we only see statistical significance for this indicator of energy rationing behavior in the hot humid and mixed humid climate type. In the mixed humid climate type where the effect was the largest, households which unplugged electronics used approximately 5% less energy than households which kept them plugged in. However, a major caveat for this finding is that households which responded "not applicable" where also significant in this climate type and used even less energy than households which responded that they unplugged electronics. We do not know how to interpret these results, we only assume that household which responded not applicable are somehow different than other households. In general this proxy seems to be rather noisy and its significance is questionable.

However, the most interesting part of this proxy was its effect on the coefficients of our other variables of education and income. In general across climate types, including this proxy decreased the significance and magnitude of the income variables. This suggests that perhaps income was an upwardly bias variable. The effects of education also changed in magnitude. Now, education appears to have a somewhat greater effect on energy consumption, with the downward trend in energy use as education increases remaining the same. Overall, however, all changes due to the inclusion of this proxy were relatively small.

K. Overall Explanatory Power of Models

Our explanatory power increases as we add regressors throughout the progression of our models. Starting with only demographic information all our climate types have an r-squared value of over 0.2 meaning that over 20 percent of the variance in household energy consumption is explained by our model. However, using this model as we demonstrated earlier, our coefficients are biased and some of what we are capturing is physical differences in homes. By including just the variables of household size and home type, as we do in our second regression, our overall explanatory power nearly doubles in most climate groups and makes our coefficients of our previous variables less biased. Thus it is apparent that size does in fact matter for household energy demand. When we include measures of home efficiency in our third model our overall explanatory power increases to a little over half of the variance in our dependent variable, energy consumption, for most climate types. Finally our last regression adding the proxy for energy rationing behavior increases our overall explanatory power in a very modest way. If our proxy is reliable this would suggest that once demographic, size, and relative efficiency variables are accounted for then household behavior has a small effect on total energy consumption.

VII. CONCLUSIONS

Our regression model reveals several factors that can contribute to inflated energy demand. Climate proved to be a major contributing factor for energy demand. Our proxy for environmental concern and behavioral changes showed little significance in altering a household's total demand. In considering the differences between the American household market and those of other countries, this model most likely lacks external validity. There are many nuanced differences, such as rural and urban composition, which vary between countries, so this model should be applied to foreign households reservedly. Although we looked at the technical decomposition of household energy demand, a model which also considers market factors like marginal fuel price and price differentials could reveal what, if any, impact the HVAC market has on households. As heating and cooling fuel produce indirect utility, it would be difficult to model such factors without specialized indirect utility functions.

In order to cultivate a more environmentally friendly housing market, policy could be enacted towards encouraging growth in more energy efficient bay areas, while discouraging population movement towards colder and more energy intensive climates, such as in the northern states. Cognizant of the effect of home ownership on energy demand, future policy should consider the environmental implications of indirect tax strategy such as the home mortgage interest deduction rate. More affordable housing could see people reinvest that savings into larger houses. Our model has shown square footage to be one of the most significant determinants of household energy demand. These shifts in policy could be enacted relatively easily, and would help in reshaping the United States housing market towards a less energy intensive structure.

VIII. References

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IX. APPENDIX

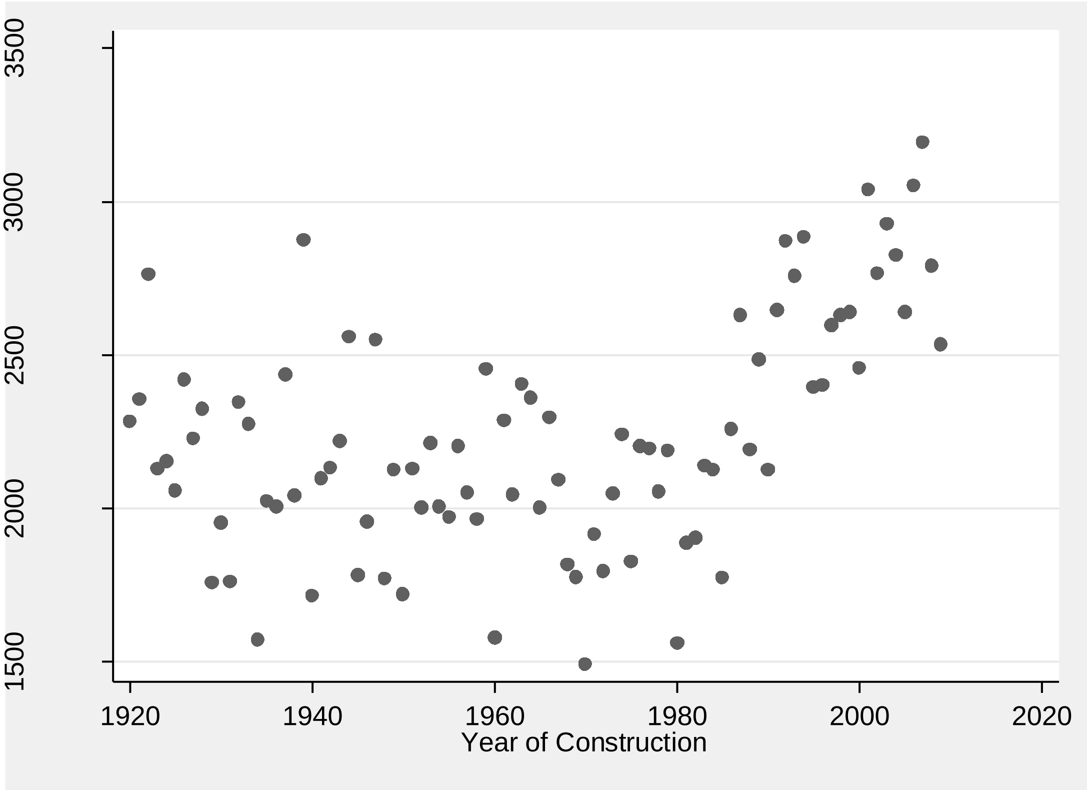

Figure 1: Average Housing Size by Year

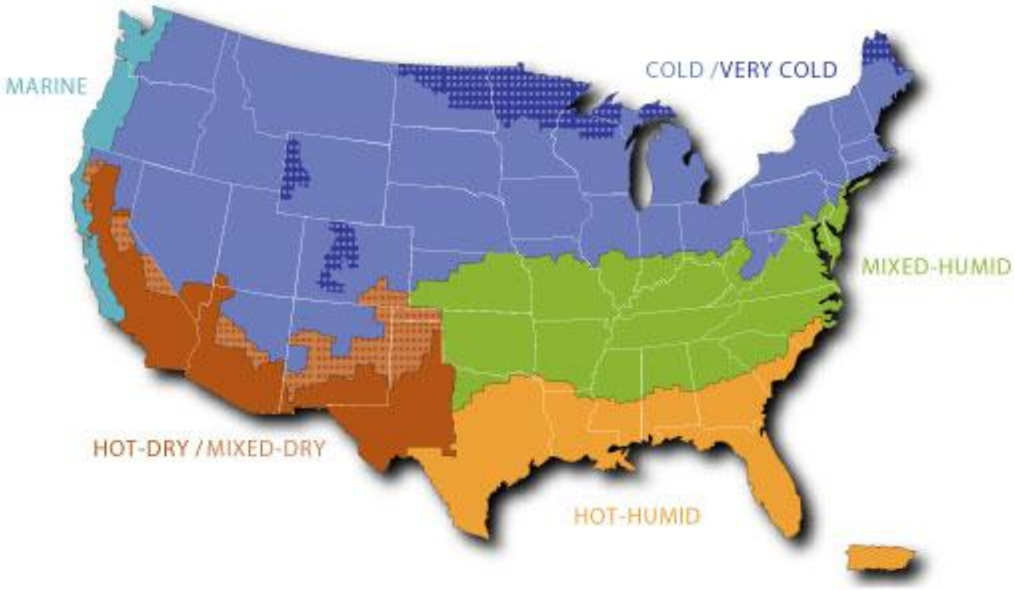

Figure 2: Division of United States by Climate Region

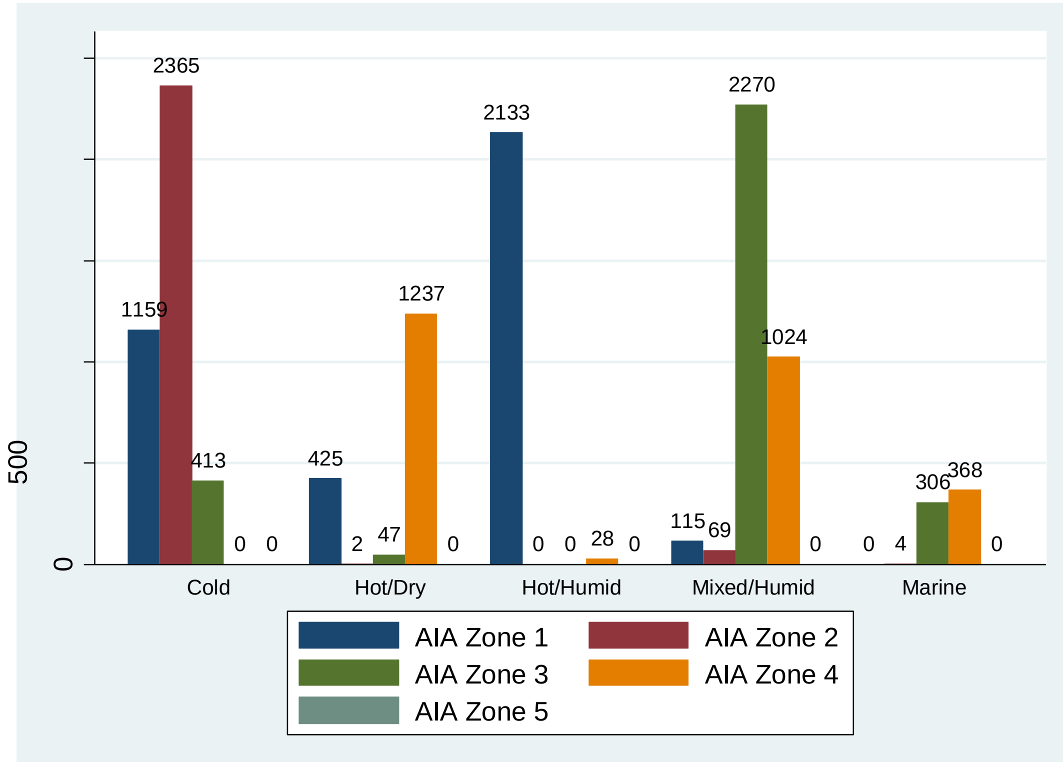

Figure 3: Composition of Climate Type by AIA Zone

Table 1: Results for Hot/Dry Climate

VARIABLES	lnBTU	lnBTU2	lnBTU3	lnBTU4
renter	-0.458***	0.0778**	0.0841***	0.0841***
	-0.0304	-0.0305	-0.03	-0.03
incomebt20_40thou	0.0459	-0.00273	0.00325	0.0021
	-0.0462	-0.0387	-0.0373	-0.0374
incomebt40_60thou	0.111**	-0.00725	0.00996	0.00787
	-0.0458	-0.0381	-0.037	-0.0371
incomebt60_80thou	0.162***	0.0288	0.0288	0.0276
	-0.0526	-0.0453	-0.0437	-0.0437
incomebt80_100thou	0.254***	0.0686	0.0792*	0.0779*
	-0.0591	-0.0484	-0.0468	-0.0468
incomegreater100thou	0.361***	0.127***	0.131***	0.130***
	-0.0483	-0.0416	-0.0409	-0.0412
hsdiploma	0.0739	0.0516	0.0261	0.0258
	-0.048	-0.0401	-0.039	-0.039
somecollege	0.0563	0.0326	-0.0126	-0.0129
	-0.0451	-0.038	-0.0367	-0.0366
collegeandbeyond	-0.0663	-0.055	-0.0925**	-0.0934**
	-0.0493	-0.0415	-0.0399	-0.0398
lnTOTSQFT		0.392***	0.376***	0.375***
		-0.0269	-0.0272	-0.0272
mobile		-0.0213	0.0252	0.0262
		-0.0559	-0.057	-0.0568
singleattached		-0.330***	-0.301***	-0.300***
		-0.0549	-0.0527	-0.0527
aptsmall		-0.331***	-0.295***	-0.296***
		-0.0522	-0.0502	-0.0503
aptbig		-0.567***	-0.513***	-0.512***
		-0.0439	-0.0454	-0.0454
heatsteam			0.264*	0.267*
			-0.148	-0.149
heatpump			-0.0853**	-0.0845**
			-0.0429	-0.0428
builtinelectric			-0.337***	-0.337***
			-0.11	-0.11
pipelessfurnace			-0.0665	-0.0683
			-0.0551	-0.0551
builtinroomheater			-0.057	-0.0586
			-0.045	-0.0451
fireplace			-0.442***	-0.442***
			-0.151	-0.153

portelectricheat			-0.365***	-0.366***
			-0.0574	-0.0574
portkerosineheat			-0.113	-0.114
			-0.35	-0.35
cookstoveheat			-0.146	-0.144
			-0.137	-0.137
otherheat			0.0521	0.0499
			-0.19	-0.191
notappheat			-0.315***	-0.316***
			-0.041	-0.0412
windowair			0.0394	0.0402
			-0.0349	-0.0352
bothair			0.0632	0.064
			-0.0684	-0.0687
adquatinsulated			-0.0911***	-0.0910***
			-0.0289	-0.0289
wellinsulated			-0.0702**	-0.0702**
			-0.0302	-0.0303
d1950			-0.0138	-0.0132
			-0.0455	-0.0454
d1960			-0.0509	-0.0518
			-0.0452	-0.0453
d1970			0.01	0.00909
			-0.0448	-0.0449
d1980			-0.135***	-0.136***
			-0.0468	-0.0469
d1990			-0.0896*	-0.0903**
			-0.0459	-0.046
d2000			-0.0564	-0.0578
			-0.0513	-0.0514
unplug				-0.0136
				-0.0259
naplug				-0.0254
				-0.0363
Constant	10.96***	8.168***	8.470***	8.489***
	-0.0498	-0.203	-0.21	-0.211
Observations	1,636	1,636	1,636	1,636
R-squared	0.211	0.466	0.513	0.514

Table 2: Results for Cold Climate

VARIABLES	lnBTU	lnBTU2	lnBTU3	lnBTU4
renter	-0.444***	-0.0289	-0.0450**	-0.0477**
	-0.0223	-0.0242	-0.0227	-0.0227
incomebt20_40thou	0.0870***	0.000212	0.000822	-0.00301
	-0.0304	-0.0272	-0.0238	-0.024
incomebt40_60thou	0.119***	-0.0211	-0.0219	-0.0272
	-0.0323	-0.0288	-0.0255	-0.0259
incomebt60_80thou	0.159***	0.00744	0.00738	0.000942
	-0.0327	-0.0295	-0.0271	-0.0274
incomebt80_100thou	0.266***	0.0759**	0.0758**	0.0696**
	-0.0356	-0.0321	-0.03	-0.0302
incomegreater100thou	0.392***	0.155***	0.153***	0.146***
	-0.0323	-0.0302	-0.0278	-0.0281
hsdiploma	0.0236	0.0187	-0.011	-0.0129
	-0.0399	-0.0345	-0.0301	-0.03
somecollege	0.0408	0.0254	0.00958	0.00577
	-0.0392	-0.034	-0.03	-0.0298
collegeandbeyond	0.00526	-0.00807	-0.0258	-0.0288
	-0.0408	-0.0359	-0.0317	-0.0316
lnTOTSQFT		0.297***	0.282***	0.281***
		-0.0205	-0.0186	-0.0187
mobile		0.0158	0.0404	0.0374
		-0.0357	-0.0348	-0.0349
singleattached		-0.173***	-0.156***	-0.156***
		-0.0264	-0.0241	-0.0241
aptsmall		-0.0769**	-0.107***	-0.109***
		-0.0385	-0.0347	-0.0348
aptbig		-0.480***	-0.412***	-0.411***
		-0.0364	-0.0336	-0.0336
heatsteam			0.143***	0.144***
			-0.0185	-0.0186
heatpump			-0.371***	-0.371***
			-0.0526	-0.0528
builtinelectric			-0.614***	-0.614***
			-0.0421	-0.0419
pipelessfurnace			0.048	0.0491
			-0.0939	-0.093
builtinroomheater			0.00109	0.000383
			-0.0466	-0.0464
heatstove			-0.426**	-0.425**
			-0.182	-0.182

fireplace			-0.0383	-0.0485
			-0.0822	-0.0809
portelectricheat			-0.509***	-0.509***
			-0.0994	-0.1
portkerosineheat			-0.427***	-0.439***
			-0.106	-0.109
cookstoveheat			0.128	0.12
			-0.0861	-0.0833
otherheat			-0.257	-0.255
			-0.166	-0.167
notappheat			-1.036***	-1.039***
			-0.218	-0.218
windowair			0.02	0.0195
			-0.0178	-0.0178
bothair			0.0311	0.031
			-0.0431	-0.0435
adquatinsulated			-0.0645***	-0.0645***
			-0.019	-0.019
wellinsulated			-0.117***	-0.116***
			-0.0205	-0.0204
d1950			0.00105	0.000527
			-0.0225	-0.0225
d1960			-0.0243	-0.0254
			-0.0243	-0.0243
d1970			-0.0654***	-0.0671***
			-0.0219	-0.0219
d1980			-0.114***	-0.114***
			-0.0237	-0.0237
d1990			-0.0551**	-0.0551**
			-0.0239	-0.0239
d2000			-0.143***	-0.145***
			-0.0254	-0.0254
unplug				-0.014
				-0.0165
naplug				-0.0410*
				-0.0245
Constant	11.44***	9.293***	9.556***	9.587***
	-0.041	-0.161	-0.149	-0.151
Observations	3,794	3,794	3,794	3,794
R-squared	0.232	0.397	0.52	0.521

Table 3: Results for Hot/Humid Climate

VARIABLES	lnBTU	lnBTU2	lnBTU3	lnBTU4
renter	- 0.346***	0.0714**	0.0682**	0.0658**
	-0.0278	-0.0333	-0.0327	-0.0327
incomebt20_40thou	0.0369	-0.00087	0.011	0.0102
	-0.0357	-0.0306	-0.0299	-0.0298
incomebt40_60thou	0.211***	0.0822**	0.101***	0.100***
	-0.0397	-0.0348	-0.0343	-0.0343
incomebt60_80thou	0.223***	0.0171	0.0602	0.0594
	-0.0438	-0.0381	-0.0367	-0.0368
incomebt80_100thou	0.448***	0.165***	0.185***	0.181***
	-0.0462	-0.042	-0.0408	-0.0411
incomegreater100thou	0.552***	0.227***	0.270***	0.267***
	-0.0434	-0.0379	-0.0382	-0.0384
hsdiploma	0.00846	-0.0352	-0.0322	-0.0308
	-0.0442	-0.0397	-0.0377	-0.0378
somecollege	0.0209	-0.0132	-0.00962	-0.0101
	-0.0429	-0.0385	-0.0372	-0.0371
collegeandbeyond	-0.0796*	-0.122***	-0.110***	-0.110***
	-0.0465	-0.0414	-0.0404	-0.0402
lnTOTSQFT		0.407***	0.431***	0.430***
		-0.0258	-0.026	-0.026
mobile		-0.00616	0.0828**	0.0814**
		-0.0387	-0.0409	-0.0407
singleattached		-0.218***	-0.202***	-0.204***
		-0.0455	-0.0439	-0.0438
aptsmall		-0.365***	-0.313***	-0.311***
		-0.0473	-0.0478	-0.0478
aptbig		-0.469***	-0.411***	-0.411***
		-0.0412	-0.0413	-0.0411
heatsteam			0.0931	0.091
			-0.308	-0.306
heatpump			-0.197***	-0.199***
			-0.0239	-0.0238
builtinelectric			-0.13	-0.125
			-0.0825	-0.0825
pipelessfurnace			0.125	0.127
			-0.131	-0.131
builtinroomheater			0.0921	0.0874
			-0.0683	-0.0683
fireplace			0.191	0.189

			-0.136	-0.127
portelectricheat			-0.160***	-0.163***
			-0.0539	-0.0542
portkerosineheat			-0.177	-0.17
			-0.302	-0.3
cookstoveheat			0.21	0.205
			-0.133	-0.135
otherheat			-0.0834	-0.0841
			-0.0988	-0.099
notappheat			-0.357***	-0.359***
			-0.0501	-0.05
windowair			0.00365	0.00549
			-0.0427	-0.0429
bothair			-0.0259	-0.0238
			-0.1	-0.1
adquatinsulated			-0.0189	-0.0178
			-0.0277	-0.0277
wellinsulated			-0.0439	-0.0438
			-0.0283	-0.0283
d1950			-0.0592	-0.0552
			-0.0477	-0.0477
d1960			-0.106**	-0.104**
			-0.052	-0.0519
d1970			-0.163***	-0.160***
			-0.0446	-0.0445
d1980			-0.169***	-0.166***
			-0.0442	-0.0442
d1990			-0.163***	-0.160***
			-0.0461	-0.0461
d2000			-0.234***	-0.233***
			-0.0438	-0.0437
unplug				-0.0394*
				-0.0237
naplug				-0.0479
				-0.0325
Constant	10.86***	7.999***	8.017***	8.062***
	-0.0432	-0.193	-0.202	-0.203
Observations	2,115	2,115	2,115	2,115
R-squared	0.217	0.413	0.463	0.464

Table 4: Results for Mixed/Humid Climate

VARIABLES	lnBTU	lnBTU2	lnBTU3	lnBTU4
renter	-0.396***	-0.00599	-0.0049	-0.00716
	-0.0217	-0.0241	-0.0224	-0.0224
incomebt20_40thou	0.0694**	0.0184	0.0113	0.00545
	-0.0292	-0.0264	-0.0236	-0.0236
incomebt40_60thou	0.147***	0.0581**	0.0510**	0.0443*
	-0.0304	-0.0273	-0.0242	-0.0242
incomebt60_80thou	0.225***	0.133***	0.114***	0.108***
	-0.0336	-0.0301	-0.0271	-0.0271
incomebt80_100thou	0.296***	0.156***	0.149***	0.141***
	-0.037	-0.0339	-0.0308	-0.0311
incomegreater100thou	0.444***	0.235***	0.223***	0.216***
	-0.0328	-0.0303	-0.0277	-0.0278
hsdiploma	-0.0610*	-0.0862***	-0.0651**	-0.0720***
	-0.0317	-0.0298	-0.0264	-0.0262
somecollege	-0.0452	-0.0943***	-0.0478*	-0.0588**
	-0.0317	-0.0299	-0.0264	-0.0262
collegeandbeyond	-0.0848**	-0.114***	-0.0827***	-0.0917***
	-0.0334	-0.0316	-0.028	-0.0278
lnTOTSQFT		0.331***	0.347***	0.346***
		-0.018	-0.017	-0.017
mobile		-0.0677**	0.000227	-0.00336
		-0.0345	-0.0326	-0.0325
singleattached		-0.125***	-0.148***	-0.150***
		-0.0318	-0.0277	-0.0275
aptsmall		-0.100**	-0.194***	-0.195***
		-0.0454	-0.0416	-0.0416
aptbig		-0.341***	-0.398***	-0.399***
		-0.0323	-0.0302	-0.0301
heatsteam			0.177***	0.179***
			-0.0289	-0.0288
heatpump			-0.299***	-0.301***
			-0.0191	-0.019
builtinelectric			-0.407***	-0.412***
			-0.0451	-0.0449
pipelessfurnace			-0.117	-0.115
			-0.11	-0.112
builtinroomheater			0.0176	0.0235
			-0.0468	-0.0464
heatstove			-0.544***	-0.539***
			-0.0445	-0.0446

fireplace			-0.0929	-0.0987
			-0.0936	-0.0957
portelectricheat			-0.423***	-0.423***
			-0.0649	-0.0639
portkerosineheat			-0.506***	-0.505***
			-0.149	-0.149
cookstoveheat			-0.222	-0.237
			-0.215	-0.197
otherheat			-0.170**	-0.162**
			-0.0852	-0.0825
notappheat			-2.694***	-2.654***
			-0.0416	-0.0435
windowair			0.0728***	0.0723***
			-0.0244	-0.0244
bothair			0.160***	0.160***
			-0.0369	-0.037
adquatinsulated			-0.0573***	-0.0567***
			-0.0208	-0.0207
wellinsulated			-0.0845***	-0.0808***
			-0.0221	-0.0221
d1950			-0.0833***	-0.0813***
			-0.0277	-0.0275
d1960			-0.0314	-0.0325
			-0.027	-0.027
d1970			-0.152***	-0.153***
			-0.0281	-0.028
d1980			-0.179***	-0.179***
			-0.0303	-0.0303
d1990			-0.166***	-0.167***
			-0.0259	-0.0258
d2000			-0.208***	-0.208***
			-0.0264	-0.0264
unplug				-0.0478***
				-0.0172
naplug				-0.0979***
				-0.0232
Constant	11.32***	8.913***	8.988***	9.054***
	-0.0326	-0.14	-0.135	-0.136
Observations	3,365	3,365	3,365	3,365
R-squared	0.217	0.376	0.506	0.509

Table 5: Results for Marine Climate

VARIABLES	lnBTU	lnBTU2	lnBTU3	lnBTU4
renter	-0.559***	0.0944	0.0994*	0.0991*
	-0.047	-0.0574	-0.0574	-0.0574
incomebt20_40thou	-0.0275	-0.0192	-0.0209	-0.0205
	-0.0862	-0.0626	-0.0601	-0.0601
incomebt40_60thou	0.153*	0.0936	0.0841	0.0851
	-0.0824	-0.0617	-0.0607	-0.0613
incomebt60_80thou	0.171*	0.0644	0.0587	0.058
	-0.0881	-0.069	-0.0701	-0.0702
incomebt80_100thou	0.281***	0.142**	0.113*	0.111
	-0.0912	-0.0701	-0.0681	-0.0684
incomegreater100thou	0.488***	0.228***	0.183***	0.183***
	-0.0843	-0.0648	-0.0652	-0.0658
hsdiploma	0.266**	0.172*	0.172*	0.172*
	-0.106	-0.0917	-0.091	-0.0901
somecollege	0.0896	0.0281	0.0223	0.0213
	-0.0987	-0.0881	-0.0874	-0.0861
collegeandbeyond	-0.081	-0.0855	-0.0956	-0.0968
	-0.102	-0.0904	-0.0902	-0.0888
lnTOTSQFT		0.472***	0.462***	0.462***
		-0.0426	-0.0448	-0.0449
mobile		0.0928	0.112	0.113
		-0.0826	-0.0921	-0.0923
singleattached		-0.195***	-0.176***	-0.176***
		-0.0642	-0.0662	-0.0664
aptsmall		-0.413***	-0.356***	-0.357***
		-0.0877	-0.0873	-0.0872
aptbig		-0.580***	-0.506***	-0.507***
		-0.0596	-0.0628	-0.0634
heatsteam			0.0506	0.0561
			-0.123	-0.125
heatpump			-0.0979	-0.0982
			-0.0767	-0.0772
builtinelectric			-0.212***	-0.210***
			-0.0573	-0.057
pipelessfurnace			-0.0733	-0.0746
			-0.0864	-0.0865
builtinroomheater			-0.0156	-0.0165
			-0.0935	-0.0938
fireplace			0.0143	0.0105
			-0.0478	-0.0488

portelectricheat			-0.153*	-0.155*
			-0.0855	-0.0856
otherheat			-0.166***	-0.163***
			-0.058	-0.0612
notappheat			-0.323***	-0.322***
			-0.0728	-0.0729
windowair			0.0409	0.0404
			-0.0456	-0.0457
bothair			-0.168	-0.165
			-0.106	-0.103
adquatinsulated			0.0215	0.0203
			-0.0468	-0.0463
wellinsulated			0.0124	0.0101
			-0.0531	-0.0525
d1950			0.0396	0.0393
			-0.066	-0.066
d1960			0.0985	0.0974
			-0.0625	-0.0626
d1970			0.00992	0.00846
			-0.0689	-0.0689
d1980			-0.00793	-0.00747
			-0.0634	-0.063
d1990			-0.013	-0.0119
			-0.0687	-0.0687
d2000			-0.049	-0.0498
			-0.0741	-0.0739
unplug				0.0156
				-0.0485
naplug				0.00114
				-0.0711
Constant	10.90***	7.486***	7.595***	7.589***
	-0.106	-0.325	-0.348	-0.347
Observations	644	644	644	644
R-squared	0.306	0.577	0.6	0.6

Table 6: Definition of Variable Terms

Variable Name	Variable Description
renter	Renter status
incomebelow20thou	Income is below $20,000
incomebt20_40thou	Annual income is between $20,000 - $40,000
incomebt40_60thou	Annual income is between $ 40,000 - $60,000
incomebt60_80thou	Annual income is between $ 60,000 - $80,000
incomebt80_100thou	Annual income is between $ 80,000 - $100,000
incomegreater100thou	Annual income is greater than $100,000
lesshs	Householder has completed less than high school
hsdiploma	Householder has completed high school or GED
somecollege	Householder has completed some college
collegeandbeyond	Householder has completed at least college
lnTOTSQFT	log of the total square feet of the home
mobile	Home is a mobile home
singledetached	Home is a single detached home
singleattached	Home is a single attached home
aptsmall	Home is in an apartment building between 2-4 units
aptbig	Home is an apartment building with 5+ units
b41950	Home was built before 1950
d1950	Home was built during the 1950's
d1960	Home was built during the 1960's
d1970	Home was built during the 1970's
d1980	Home was built during the 1980's
d1990	Home was built during the 1990's
d2000	Home was built during the 2000's
centralair	Home uses a central air conditioning unit
windowair	Home uses a window air conditioning unit
bothair	Home uses both a central and window air conditioning unit
noappair	Householder responded "not applicable" for type of cooling equipment used
heatsteam	Steam or hot water heating equipment
centralfurnace	Central warm air furnace heating equipment
heatpump	Heat pump heating equipment
builtinelectric	Built in electric unit heating equipment
pipelessfurnace	Floor or wall pipeless furnace heating equipment
builtinroomheater	Built in room heater heating equipment
heatstove	Heat stove heating equipment
fireplace	Fireplace heating equipment
portelectricheat	Portable electric heaters heating equipment
portkerosineheat	Portable kerosene heaters heating equipment

cookstoveheat	Cooking stove heating equipment
otherheat	Other equipment
notappheat	Householder responded "not applicable" for type of heating equipment used
poorinsulated	Home is poorly insulated
adquatinsulated	Home is adequately insulated
wellinsulated	Home is well insulated
keepplugged	Householder keeps electronics plugged in when not in use
unplug	Householder unplugs electronics when not in use
naplug	Householder responded "not applicable" to whether they leave rechargeable electronic device chargers plugged into the wall when not in use

Table 7: Statistical Summaries of Climate Divisions

Variable	Observations	Mean	Std. Dev.	Min	Max
Cold					
TOTALBTU	3993	112678.2	58358.26	58	604612
TOTSQFT	3993	2422.76	1541.317	100	13776
Hot/Dry					
TOTALBTU	1716	67345.16	41064.44	2887	572003
TOTSQFT	1716	1835.222	1192.922	120	13580
Hot/Humid					
TOTALBTU	2173	65846.3	44172.99	321	1096083
TOTSQFT	2173	1884.532	1211.747	210	11312
Mixed/Humid					
TOTALBTU	3521	94853.05	51333.77	3020	534002
TOTSQFT	3521	2288.821	1572.532	200	16122
Marine					
TOTALBTU	680	65977.01	41458.42	4088	321747
TOTSQFT	680	1869.399	1201.529	136	10783