FACTORS INFLUENCING ENERGY CONSUMPTION AMONG MODERATELY LOW INCOME RESIDENTS IN MULTIFAMILY RENTAL APARTMENTS

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Achala Parameshwari Mosale Krishne gowda

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Approved by:

Dr. Javier Irizarry, Advisor
School of Building Construction
Georgia Institute of Technology

Rick Porter
School of Building Construction
Georgia Institute of Technology

Dr. Deborah R. Phillips, CPM
School of Building Construction
Georgia Institute of Technology

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SUMMARY

Residential electricity consumption is responsible for approximately 30% of global electricity consumption. Further, residential electricity consumption in the United States of America is 25% of the total energy consumption in the United States. Hence the residential energy sector will play a critical role in the future of the electricity industry, especially given the increasing global demand for affordable electricity services, as well as the urgent need to reduce climate change emissions from the electricity sectors.

Recent studies estimate that behavioral changes can reduce residential energy consumption by about 7.4%. So, by providing more detailed feedback to consumers about their energy usage at the appliance level can potentially encourage such behavioral changes. However, achieving a better understanding of the nature of household electricity consumption is challenging, due to the heterogeneity of the residential sector, the complexity of the under-lying drivers and the lack of comprehensive data. Relevant data includes household demographics, including occupant numbers, age distributions, and income; household behavior such as how often occupants use certain appliances and the interest and effort that they devote towards energy conservation; building types, such as the type of dwelling (free standing or unit), different appliance ownership and access to alternatives to electricity for some services such as gas for heating and cooking; and the climate zone of the households as well as the daily weather conditions. As explained before, the wide variation seen across all of these drivers' leads to considerable differences in households' electricity consumption. But data on these drivers is not always available. There has generally been only limited electricity consumption data available.

Energy Conservation has become one of the first sustainability issues to be addressed through combination of national and local government policies. Human behavior is the major link to the environmental issues like global warming. Making domestic energy consumption visible to the end users has become more challenging due to metering methods. The only commonly visible record of consumption comes in the form of quarterly bills or monthly statements, by which time the links between specific activities and the energy consumed are severely dislocated, a situation described elsewhere as similar to a supermarket not displaying any individual product prices but merely providing the shopper with a total non-itemized bill at the checkout. Such issues create a negative effect on awareness towards sustainability.

Many studies have proven that giving feedback on human behavior has significantly affected the energy consumption. To most consumers in developed countries, the fuel used within homes has become, to a large extent, an invisible resource. So, there should be some policy to guide consumers and to make them understand the importance of energy saving.

Several test statistics procedures were performed to understand the relationship between residents' behavior and energy consumption: Impact of indoor and outdoor temperature on energy consumption, Impact of residents' activities and awareness on energy consumption, and Impact of all variables in the study on energy consumption.

CHAPTER 1. INTRODUCTION

Residential electricity consumption is responsible for approximately 30% of global electricity consumption. Further, residential electricity consumption in the United States of America is 25% of the total energy consumption in the United States (EIA, 2016). Hence the residential energy sector will play a critical role in the future of the electricity industry, especially given the increasing global demand for affordable electricity services, as well as the urgent need to reduce climate change emissions from the electricity sectors.

Recent studies estimate that behavioral changes can reduce residential energy consumption by about 7.4% (Magali A. Delmasa, Jan 27, 2015). So, by providing more detailed feedback to consumers about their energy usage at the appliance level can potentially encourage such behavioral changes. (Victor Chen M. A., Nov 2014)

The drivers of electricity consumption in these residential sectors include climate, demographics, housing stock, age of the building, building types, household appliances and behavioral aspects.

The respective influence of these is not well researched. There has also been considerable change in these elements over recent decades. In particular, more energy efficient technologies for lighting, communications, space heating and cooling, cooking, refrigeration and water heating have advanced rapidly in the last decade. Along with more energy efficient building standards and other energy efficiency oriented policy efforts, these corresponding developments seem likely to have contributed to decreased residential electricity demand in a number of localities over recent years. Technology innovation is also involved in enabling the transition to a low-carbon energy system (Agency, 2015).

The components of electricity consumption in the home may be classified in broad terms as ‘‘predictable’’, ‘‘moderately predictable’’ and ‘‘unpredictable’’. The former occur when the building is unoccupied or the occupants are asleep (small cyclic loads for example from refrigeration appliances and steady loads from security lighting and items on standby such as TVs, and VCRs). It is affected by both occupancy and external influences (e.g. seasonal/weather variations). The ‘‘moderately predictable’’ consumption relates to the habitual behavior patterns of the residents. For example, many people watch TV programs at regular times each day/week and switch lights on/off each weekday morning as they rise and then leave for work. Lastly ‘‘unpredictable’’ consumption describes the majority of domestic energy use; it tends to be irregular occurring at the users discretion, for example when the occupant wants to cook food or operate the clothes- or dish-washing machine. (G. Wood, 2003)

These three types of consumption may be found in most households, but this simple classification alone cannot explain why energy-consumption and electrical load profiles are so different between otherwise similar households. Understanding the activities that affect the consumption is important. For instance, variations between households' unpredictable electricity consumption result from variations in micro-level activities, e.g. differences in the length of time taken to do each activity, in cooking and home laundry habits as well as in the availability of appliances. (Lutzenhiser, November 1993)

A better understanding of how various factors influence residential electricity demand can assist in understanding possible future developments in the sector, as well as assist in identifying opportunities to improve outcomes through targeted household and broader policy efforts. For instance, such information can provide guidance to policy makers on the impact of different housing and household trends on local residential electricity demand and assist in forecasting the potential impacts of planning changes, housing retrofits and use of new energy efficient appliances under different possible government policy measures. Electricity utilities could use such insights to improve their planning and operational processes, while households could also benefit in better managing their electricity costs through an improved understanding of how decisions about what housing and appliances they choose can impact on their electricity bills, and what opportunities they might have to reduce consumption.

However, achieving a better understanding of the nature of household electricity consumption is challenging, due to the heterogeneity of the residential sector, the complexity of the under-lying drivers and the lack of comprehensive data. Relevant data includes household demographics, including number of occupants, age distributions, and income; household behavior such as how often occupants use certain appliances and the interest and effort that they devote towards energy conservation; building types, such as the type of dwelling (free standing or unit), different appliance ownership and access to alternatives to electricity for some services such as gas for heating and cooking; and the climate zone of the households as well as the daily weather conditions. As explained before, the wide variation seen across all of these drivers' leads to considerable differences in households' electricity consumption. But data on these drivers is not always available. There has generally been only limited electricity consumption data available.

1.1 Factors affecting energy consumption

Many researchers have proven that energy consumption is mainly dependent on appliances used (Blakeley, 1977) and consumers' income (Newman D. K., 1968). While some researchers use different methods to decrease energy usage like by providing feedback to individuals about their past energy consumption (Kohlenberg, 1976) and attempting to change their attitudes towards energy consumption (Team, 1977). At the same time, some researchers have also concluded that a consumer's knowledge about energy consumption is not an important variable in consumption behavior (Hayes, 1977).

These contradictory findings have lead many more researchers to get interested in this subject.

Factors which influence energy consumption are: appliances used, temperature, consumers' income, consumers' life style, number of households, place, type of house and its size, problem in the appliances/ HVAC system, low maintenance of house, and so on.

Human behavior varies from place to place and time to time. Previously, not all women were working, they used to spend more time at home than outside, they used to cook regularly. Not many appliances were introduced. Later, as time changed, people started using appliances for cooking, cleaning, cooling, washing and drying. But again, these appliances were not that energy efficient. More energy consumption was due to these appliances usage. Now, as technology improved, appliances are certified and more energy efficient.

Working towards sustainability, human behavior like cooking time, frequency of using each appliance, setting temperature, their social life, attitude towards sustainability and so on, plays a major role.

The studies in which strong relationships were shown between the model components and behavior were done under conditions which should have augmented prediction. Fishbein and Ajzen suggested that the predictability of the behavior is moderated by the degree to which the behavior is controlled by external factors (Ajzen, 1975). In some studies, situational variables may have limited the completion of intended behavior (Newman J. E., 1974). Ajzen and Fishbein (Fishbein, 1977)also suggested that multiple act criteria are more difficult to predict than a single act condition. Most of the studies have attempted to predict simple behavior, analogous to a single act condition (Greenab, 1982).

1.2 Objective, goals and research covering

Recent studies on human behavior on energy consumption have shown that human behavior is at least as important as the physical characteristics of a building in influencing energy use, and that carbon emissions from dwellings are most sensitive to internal temperature changes, largely dependent on human behavior. By understanding the interaction between human behavior and the physical variables of buildings they occupy, we can untie the complex relationships affecting energy use and get a clearer idea where energy and emissions savings can be made (Kelly, 2013). <u>The objective of this study is to identify and classify two specific characteristic: thermostat setting and occupant behavior of either opening or closing the windows which influence electricity consumption in multifamily moderately low income housing industry, and to estimate the impact of these behaviors.</u>

To make the housing industry more sustainable, there is a need for more deliberation and better communication between decision-makers of housing industry, technical experts who are involved in making household appliances, other stakeholders like government, and the consumers. This study will also help reduce this communication gap, thus supporting the policy makers of moderately low income residents within the multifamily housing industry in planning of subsidies and policies accordance with the necessity of different age group population. (NAA, NMHC, IREM, 2015)

This research addresses thermostat setting and occupant behavior of either opening or closing the windows and variability in consumption; public opinion and conservation attitudes; consumer knowledge and the social contexts of consumption;.

1.3 Hypothesis

"Thermostat setting and occupant actions of either opening or closing the windows affects the energy consumption among multifamily moderately low income renters"

1.4 Drawbacks and limitations

The drivers along with given the complexity of attitudes, behaviors and the relationship between the two, it is not surprising that this study is not reflected in significant shifts in behavior. Limited data have posed significant challenges for reliable and useful residential electricity demand modelling. Using aggregated or partial data consisting of either social economic information or behavior to model will limit the outcomes.

Also, this research is more concerned with moderately low income housing industry in the State of Georgia. This does not include population of different income category. More details of households' information on lifestyle, work culture, type of vehicle they own (electric/ fuel), knowledge on efficient power utilization would provide better understanding and result for the study.

Along with tenant's behavior, some other factors which influence/ impact on sustainability are: community employee's behavior, envelop leakage, equipment's condition, fluctuation of daily temperature. Due to limitation of time, this study only focuses on outcomes related to electricity consumption among moderately low income residents in multifamily rental housing.

CHAPTER 2. LITERATURE REVIEW

2.1 Importance of human behavioral study in sustainability

Energy Conservation has become one of the first sustainability issues to be addressed through combination of national and local government policies. Human behavior is the major link to the environmental issues like global warming. Making domestic energy consumption visible to the end users has become more challenging due to metering methods. The only commonly visible record of consumption comes in the form of quarterly bills or monthly statements, by which time the links between specific activities and the energy consumed are severely dislocated, a situation described elsewhere as akin to a supermarket not displaying any individual product prices but merely providing the shopper with a total non-itemized bill at the checkout (Stern, 1984). Such issues create a negative effect on awareness towards sustainability.

Many studies have proven that giving feedback on human behavior has significantly affected the energy consumption. Energy consumption feedback presents a more consensual view on the positive role feedback can have, although it fails to pinpoint which types of feedback are most effective (Farhar, 1989). Research done by Gwendolyn Brandon and Alan Lewis shows that the multiple regression analysis reveals that the feedback combined, compared with the control conditions and environmental attitudes and behavior, have a marginal statistically significant influence on the total percentage difference of energy consumed in kWh hours for that period of study (LEWIS, 1999).

To most consumers in developed countries, the fuel used within homes has become, to a large extent, an invisible resource. So, there should be some policy to guide consumers and to make them understand the importance of energy saving.

2.2 Fishbein and Ajzen measures

(Green, 1982)Four behaviors, two specific to summer electricity consumption and two which apply in all seasons:

I. Raising the temperature of the residence
II. Using a fan instead of an air conditioner
III. Lowering the temperature of the water heater
IV. Conserving energy at the residence

For each such behavior, a number of Fishbein-Ajzen model components were measured.

A single item was included to assess the behavioral intention associated with each of the above mentioned four behaviors. For instance, behavioral intention (BI) statement is, "How likely is it that you will use a fan instead of an air conditioner during hot weather?" which had five responses available ranging from "Very Likely" to "Very Unlikely".

For every behavioral intention, various beliefs were measured which, in combination with their evaluation, composed a measure of the A_B component. The two consequences for three of the behaviors were "the reduction of utility costs" and "the conservation of energy." A third consequence, "will cause you inconveniences," was substituted for "conservation of energy" when the behavior was conserving energy. The first two outcomes were assessed because they are direct and are measurable results of engaging in the conservation behaviors investigated. They also summarized the outcomes of a number of specific behaviors. The third outcome was included because the authors felt that consumers believe that conserving energy leads to inconvenience. The results found for this concluding hypothesis (Seligman, 1979).

An example of the behavior consequence belief subcomponent was "How likely is it that using a fan instead of an air conditioner during hot weather will reduce your utility costs?" same type of responses was given as option to choose.

The second subcomponent of A_B was the evaluation subcomponent. For each behavioral consequence an evaluation was made. An example of the evaluation was "Reducing your utility costs is how good or bad?" which had five response option ranging from "Very good" to "Very Bad". The A_B and intention components were patterned after those used previously by Davidson and Jaccard (Davidson. A. R., 1971).

2.3 Different modeling techniques

When studying the different modelling approaches for residential electricity consumption. Remarkably, they are all critically limited based on the available data. There are major three modeling approaches for electricity consumption. They are, the top-down approach, which focuses on the interaction between electricity consumption and economic metrics at a high level scale using aggregated socio-economic data. This type of study presents a stimulus with short and uncertain clarity which makes the study/value vague. (Fernandez J, 2009)

The residential electricity consumption in Portugal is done using this approach. The socio-economic factor and change in building stock is the major influencer in the energy consumption according to the study; next is bottom-down approach, which statistically analyses household survey data and electricity consumption reading. (M. Kavgica, 21 January 2010) Study of energy consumption model in Europe is the best example for this approach; and the physical model approach, which models physically measured data on specific dwellings, appliances and technologies. Most of the energy analyst use this approach for the study of energy consumption. All three approaches have their strengths and weaknesses, due to the differing nature of their input data and assessment capability.

The majority of papers focus on analyzing the socio-economic impacts of the electricity sector (USA Today, 2013). In the United States, the majority of energy consumption came critically low during recession. As there was a huge drop in the number of new home buyers. Alternately, bottom up modelling utilizes disaggregated data to estimate the impact of various factors on electricity consumption. Some bottom up approaches use samples of houses' building physics to represent larger housing stock, combining building electricity calculations with statistical methods. A considerable number of international studies have focused better understanding household electricity demand. As such the review presented here can only select a few sample studies and these are listed by the modelling approach used in the section below.

2.3.1 Top down approach

The top-down model approach uses the high-level information that a facility routinely collects regarding its activities and performance, and associates that data with the corresponding energy consumption. (Yeager Vogt PE, 2009) The econometric top-down models are primarily based on energy use in relationship to variables such as income, fuel prices, and gross domestic product to express the connection between the energy sector and economic output. They can also include general climatic conditions, such as population-weighted temperature (National Weather Services, 2005), for a nation. The econometric top-down models often lack details on current and future technological options as they rater place the importance on the macroeconomic trends and relationships observed in the past, rather than on the individual physical factors in buildings that can influence energy demand. More importantly, the reliance on past energy–economy interactions might also not be appropriate when dealing with climate change issues where environmental, social, and economic conditions might be entirely different to those previously experienced. They have no inherent capability to model discontinuous changes in technology. The best example which demonstrates top-down approach in energy consumption is (Online, 2009)"The two models for benchmarking UK domestic delivered energy". In this approach, from publicly available data, two simple models are developed to help identify the path of total delivered energy to UK households and provide benchmarks for the UK domestic sector. Both models are made to check if delivered energy in the domestic sector is on track and whether the reductions correspond with the expected impact of a more efficient domestic sector. The annual delivered energy, price, and temperature (ADEPT) model uses multiple linear regression to fit consumption data since 1970 (R 2 = 0.76). Findings indicate that with typical recent heating season temperatures of 7°C and at 2005 energy prices, average household delivered energy is estimated at 21.7 MWh (95% confidence interval = 20.8, 22.6). For every 1°C increase in heating season temperature, average household delivered energy drops by approximately 1 MWh/year. Energy price elasticity is estimated at –0.2, so that a 50% rise in energy prices corresponds to an approximate 10% decline in energy demand. But, this model failed to explain the technology changes, behavioral changes and other factors directly involved in energy consumption.

2.3.2 Bottom up approach

The bottom up approach (Victor Chen M. A., November 2014) can be well explained by the research work done in California, "What can we learn from high frequency appliance level energy metering?" In this research paper, the survey data from university housing (ENGAGE sample) is used as primary data and is matched with Residential Energy Consumption Survey (RECS) administered by the United States Energy Information Administration (EIA) to do the analysis. Later, all the results are joined together to make a solid conclusion on behavior impact on energy consumption. This study had many limitations, first as the experimental site was located at an apartment complex for graduate students and their families. Even though the sample was similar to the rest of California in terms of electricity usage, the participants are more educated than the typical California household. However, this characteristic indicates that the results are conservative. Indeed, if an educated population does not know much about appliance-level usage, it is unlikely that the rest of the population knows more. Second, for households that are away from their apartment during academic holidays, electricity usage for those households will appear much lower than normal. Third, due to technical limitations and user error, some electricity measurements were missing or recorded with some error. The bottom-up approach generally provides a good understanding of the technological drivers of electricity consumption, however it requires a large sample size and typically relies on reliable historical consumption data, which is not always available.

2.3.3 Physical model approach

Numerous traditional and emerging modelling methods have been broadly utilized electricity consumption analyses and forecasting energy consumption in different parts of the world. Some of the models which are commonly used are (Jain, 2009) time series models (majorly Grey prediction with rolling mechanism), regression models, (Alberto Hernandez Neto, 2008) detailed model simulation, artificial neural networks model and complex hybrid models.

CHAPTER 3. DATA AND DATA TREATMENT

The study is focused to analyze the effect of human behavior in energy consumption. Multifamily moderately low income apartments have been selected in the state of Georgia. Data for the time period March 2013 to September 2014 was collected through Southface energy institute. Five apartment buildings volunteered to participate in the study. However only two of them provided all required data including consumption data. Hence this study uses data from those two apartments.

The detailed house-hold characteristics of this dataset present a unique opportunity for better understanding of moderately low income household electricity consumption in the state of Georgia.

Because data was only available for two apartments, energy consumption data and secondary data of human-behavior survey has been analyzed for two apartments complexes with 71 units in total.

From a set of 151 variables, relevant variables were identified. After data cleanup[1], 24 variables have been retained for data analysis.

3.1 Secondary data

First Apartment community is located in Cordele, Georgia and is owned by Rural Housing Partnership Inc. This Low Income Housing (LIH) project has been in service since 1995 and has a total of 46 low income units, which is average for LIH properties.

[1] Data cleanup- checking the variables and removing of variables which are not useful for this particular study.

Second Apartment community is located in Rincon, Georgia in the 31326 zip code. This apartment community was built in 2012 and has 3 stories with 60 units.

Secondary data collect from Southface energy Institute includes: Age, City, Zip Code, duration of stay in the current home in years, knowledge of the certifications of current home (Moderately low income housing and green building), number of bedrooms and bathrooms, appliances used list, temperature setting in different seasons, use of fans, Space Heater, Dehumidifier, Humidifier and windows to increase the comfort level, indoor and out-door noise experience and health related questions along with Energy consumption data.

Monthly temperature data from March 2013 to September 2014 is used in the analysis (National Weather Services, 2005).

3.2 Methodology

3.2.1 Multiple linear regression

To do the behavior analysis, multiple linear regression analysis has been used. Multiple linear regression has been used, as the predictor variables (independent variables) can be controlled in this study. To get the more accurate response, the influence of more than one predictor variable is investigated. For instance, in this study, if we consider the energy consumption, it has been influenced by controlling of more than one predictor variables- size of the house, location, temperature, mind-set of the residents, health condition of the residents and so on.

The multiple linear regression models can either be used for the purpose of experimental data or for observational data from a complete randomized design.

In this study, the dependent variable is monthly energy consumption (Y) and independent variables (X) include all the secondary data which are collected from Southface Energy Institute along with monthly temperature data.

When there are more than two predictor variables (X_1, X_2, X_3, $X_4 \ldots X_n$), the regression model:

Equation 1 $$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \ldots\ldots\ldots B_n X_{in} + \varepsilon_i$$

The above model is called as first order model with more than one predictor variables. A first-order model is a linear in the predictor variables. Y_i denotes the response in the *i* th trial, and X_{i1}, X_{i2} and so on are the values of the two predictor variables in the *i* th trial. The parameters of the model are β_0, β_1, β_2 and so on, and the error term is ε_i

Assuming that E (ε_i) = 0, the regression function model is

Equation 2 $$E(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots\ldots B_n X_n$$

Analogous to simple linear regression, where the regression function $E(Y) = \beta_0 + \beta_1 X_1$ is a line, regression function (3.2) is a plane (John Neter, 1996).

Consider the following example of a multiple linear regression model with two predictor variables, X_1 and X_2:

$$Y = 30 + 5X_1 + 7X_2 + \varepsilon$$

This regression model is a first order multiple linear regression model. This is because the maximum power of the variables in the model is 1. (The regression plane corresponding to this model is shown in the figure (3.1).) Also shown is an observed data point and the corresponding random error, ε. The true regression model is usually never known (and therefore the values of the random error terms corresponding to observed data points remain unknown). However, the regression model can be estimated by calculating the parameters of the model for an observed data set. This is explained in Estimating Regression Models Using Least Squares.

Figure (3.2) shows the contour plot for the regression model the above equation. The contour plot shows lines of constant mean response values as a function of X_1 and X_2. The contour lines for the given regression model are straight lines as seen on the plot. Straight contour lines result for first order regression models with no interaction terms.

A linear regression model may also take the following form:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + B_{12} X_1 X_2 + \varepsilon$$

A cross-product term, is included in the model. This term represents an interaction effect between the two variables and interaction means that the effect produced by a change in the predictor variable on the response depends on the level of the other predictor variable(s). As an example of a linear regression model with interaction, consider the model given by the equation.

At the same time, for first-order model with more than two predictor variables, this response function is a hyperplane, which is a plane in more than two dimensions. It is no longer possible to picture this response surface, as we are able to do in above example of two predictor variables. Still the meaning of the parameters is analogous to the case of two predictor variables.

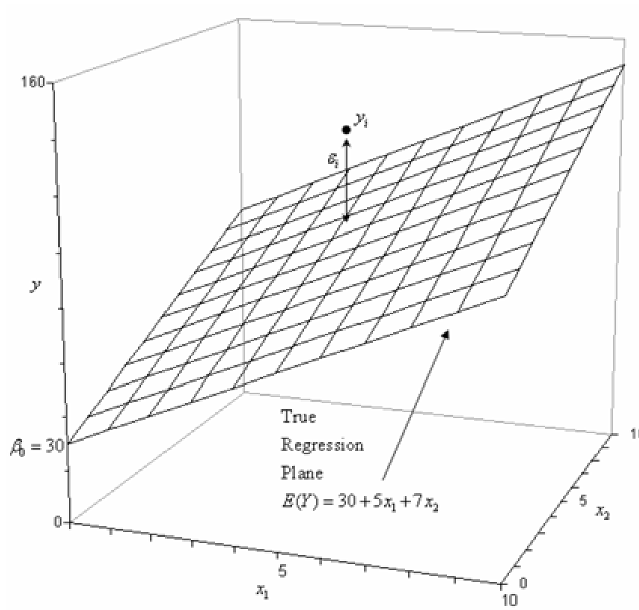


Figure 1 Regression plane for the model

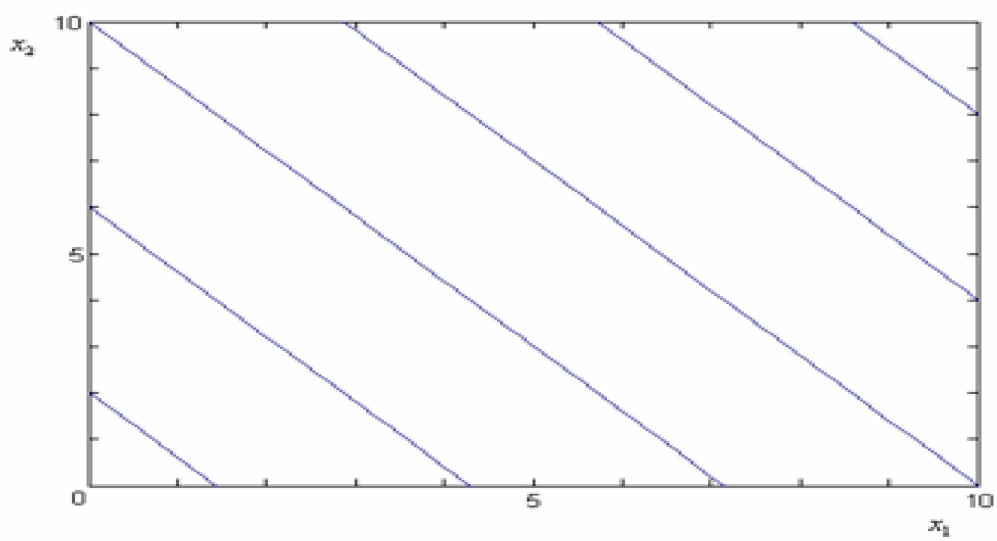


Figure 2 Contour plot for the model

3.2.1.1 Regression coefficient

In the above example, the parameter β_0= 30 is the Y intercept of the regression plane. If X_1 and X_2 both are equal to 0, then β_0= 30 represents the mean response E(Y) at X_1= 0, X_2= 0. Else, β_0 does not have any particular meaning as a separate term in the regression model.

B_1 indicates the change in the mean response E(Y) per unit increase in X_1 when X_2 is held constant and wise versa. In the above example $E(Y) = 30 + 5X_1 + 7X_2 + \varepsilon$, if X_2 is held at the level X_2= 10. The regression function is now:

$$E(Y) = 30 + 5X_1 + 7X_2 = 30 + 5X_1 \qquad X_2 = 10$$

This response function is a straight line with slope $\beta_1 = 5$. The same is true for any other values of X_2; only the intercept of the response function will differ. Therefore, $\beta_1 = 5$ indicates that the mean response E(Y) increases by 5 with a unit increase in X_1 when X_2 is constant. Hence, β_1 indicates the change in E(Y) with a unit increase in X_1 when X_2 is held constant and vice versa.

3.2.1.2 Additive effects or not to interact

When the effect of X_1 on the mean response does not depend on the level of X_2, and vice versa, the two predictor variables are said to have additive effects or not to interact. Thus, the first order regression model (equation 1) is designed for predictor variables whose effects on the mean response are additive or do not interact.

The parameters β_1 and β_2 are sometimes called partial regression coefficient because they reflect the partial effect of one predictor variable when the other predictor variables is included in the model and is held constant.

3.2.1.3 Interpretation of regression analysis

3.2.1.3.1 P-value

The p-value for each term tests the null hypothesis that the coefficient is equal to zero (no effect). A low p-value (< 0.05) indicates that one can reject the null hypothesis[2]. In other words, a predictor that has a low p-value is likely to be a meaningful addition to the model because changes in the predictor's value are related to changes in the response variable.

On the other hand, a larger (insignificant) p-value suggests that changes in the predictor are not associated with changes in the response (http://blog.minitab.com/, n.d.).

3.2.1.3.2 R-squared

R-squared is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination, or the coefficient of multiple determination for multiple regression.

[2] (In a statistical test) the hypothesis that there is no significant difference between specified populations, any observed difference being due to sampling or experimental error.

R^2 is defined as the percentage of the response variable variation that is explained by a linear model. R-squared is always between 0 and 100%:

- 0% indicates that the model explains none of the variability of the response data around its mean.
- 100% indicates that the model explains all the variability of the response data around its mean.

In general, the higher the R-squared, the better the model fits the data (Frost, 2013).

3.2.1.4 Variance inflation factors (VIF)

Variance inflation factors (VIF) measure how much the variance of the estimated regression coefficients is inflated as compared to when the predictor variables are not linearly related.

Use to describe how much multicollinearity (correlation between predictors) exists in a regression analysis. Multicollinearity is problematic because it can increase the variance of the regression coefficients, making them unstable and difficult to interpret (Minitab, 2016).

Table 1 VIF Status of predictors

VIF	**Status of predictors**
VIF = 1	Low Correlation
1 < VIF < 5	Moderately correlated
VIF > 5 to 10	Highly correlated

3.3 Data set

3.3.1 Before cleaning[3]

Table 2 Data set before cleaning

ATTRIBUTE	DATA TYPE
Date Submitted	Number
Latitude	Number
City	Text
State/Region	Text
Are you at least 18 years of age?	Number
Are you the leaseholder or utility bill account holder?	Text
City: What is your previous home's address?	Text
Zip Code: What is your previous home's address?	Number
How long did you live in your previous home?	Number
Was your previous home a green building?	Text
# Of Bedrooms: How many bedrooms were in your previous home?	Number
# Of Bathrooms: How many bathrooms were in your previous home?	Number
Was your previous home in a multifamily building?	Text
Oven/Range: Which appliances did you have in your previous home?	Text
Refrigerator: Which appliances did you have in your previous home?	Text
Dishwasher: Which appliances did you have in your previous home?	Text
Spring: To increase comfort in your previous home, did you open windows at any point during the year?	Text

[3] Cleaning- checking if all these variables are relevant and removing if they are not.

Table 2 Continued

Summer: To increase comfort in your previous home, did you open windows at any point during the year?	Text
N/A: To increase comfort in your previous home, did you open windows at any point during the year?	Text
Space Heater: To increase comfort in your previous home, did you use any of the following?	Text
Fan: To increase comfort in your previous home, did you use any of the following?	Text
Dehumidifier: To increase comfort in your previous home, did you use any of the following?	Text
Humidifier: To increase comfort in your previous home, did you use any of the following?	Text
Did you feel personally connected to other people in your previous building and development?	Text
Community Center: Please select the community areas from the list below that were available in your previous home.	Text
Playground: Please select the community areas from the list below that were available in your previous home.	Text
Green Space (Trees, Grass, Vegetation, and Courtyard): Please select the community areas from the list below that were available in your previous home.	
Pool: Please select the community areas from the list below that were available in your previous home.	Text
Recreational Facilities (Gym, Basketball Court, Etc.): Please select the community areas from the list below that were available in your previous home.	
How often did you use the community areas in your previous home?	Number
How did you feel when you were in the previous outdoor community areas?	Text

Table 2 Continued

Overall, how safe did you feel in your previous home, including outdoor community areas?	Text
Other Activity Level: (Please Describe Type of Activity, How Many Times and Length of Time): How would you describe your weekly activity level in your previous home?	Text
Unit #: What is your current home's address?	Number
City: What is your current home's address?	Text
State: What is your current home's address?	Text
Zip Code: What is your current home's address?	Number
How long have you lived in your current home?	Number
Is your current home a moderately low income development?	Text
Is your current home a green building?	Text
# Of Bedrooms: How many bedrooms and bathrooms are in your current home?	Number
Is your current home in a multifamily building?	Text
Refrigerator: What appliances do you have in your current home?	Text
Dishwasher: What appliances do you have in your current home?	Text
In-Unit Laundry: What appliances do you have in your current home?	Text
What temperature (in degrees) do you set your personal thermostat in your current home during the summer?	Number
What temperature (in degrees) do you set your personal thermostat in your current home during the winter?	Number
Fall: To increase comfort in your current home, do you open windows at any point during the year?	Text

Table 2 Continued

Winter: To increase comfort in your current home, do you open windows at any point during the year?	Text
Spring: To increase comfort in your current home, do you open windows at any point during the year?	Text
Summer: To increase comfort in your current home, do you open windows at any point during the year?	Text
Space Heater: To increase comfort in your current home, do you use any of the following?	Text
Fan: To increase comfort in your current home, do you use any of the following?	Text
Dehumidifier: To increase comfort in your current home, do you use any of the following?	Text
Humidifier: To increase comfort in your current home, do you use any of the following?	Text
Do you feel personally connected to other people in your current building and development?	Text
Community Center: Please select the community areas from the list below that are available in your current home.	Text
Playground: Please select the community areas from the list below that are available in your current home.	Text
Green Space (Trees, Grass, Vegetation, and Courtyard): Please select the community areas from the list below that are available in your current home.	Text
Vegetable Garden: Please select the community areas from the list below that are available in your current home.	Text
Picnic Tables/Outdoor Grill: Please select the community areas from the list below that are available in your current home.	Text
Walking Trails: Please select the community areas from the list below that are available in your current home.	Text

Table 2 Continued

Pool: Please select the community areas from the list below that are available in your current home.	Text
Recreational Facilities (Gym, Basketball Court, Etc.): Please select the community areas from the list below that are available in your current home.	Text
How often do you use the community areas in your current home?	Number
How do you feel when you are in your current outdoor community areas?	Text
Overall, how safe do you feel in your current home, including outdoor community areas?	Text
How would you describe your weekly activity level in your current home?	Text
Compared with your previous home, how would you rate the comfort of your current home during summer?	Text
Compared with your previous home, how would you rate the comfort of your current home during winter?	Text
Compared with your previous home, how would you rate the affordability of your current home in terms of utility costs alone?	Text
Compared with your previous home, how would you rate the affordability of your current home in terms of overall housing budget (rent + utilities)?	Text
Compared with your previous home, how would you rate your overall satisfaction with your current home in terms of both comfort and affordability?	Text
Please rate your experience with indoor noise in your current home.	Text
Please rate your experience with outdoor noise in your current home (i.e. Heating/Ventilation/Air/Conditioning (HVAC), traffic, etc.)	Text

Table 2 Continued

Overall, how do you feel about the noise in/around your home?	Text
Did you have health/medical insurance while living in your previous home?	Text
Did you purchase health insurance through Healthcare.gov or The Affordable Care Act?	Text
Did you suffer from asthma or other respiratory conditions in your previous home (bronchitis, pneumonia or lung disease)?	Text
Did you suffer from any other medical condition(s) in your previous home?	Text
Did the medical condition(s) change while you lived in your previous home?	Text
Did you take any medication (including over-the-counter and/or prescription medication) for your medical condition(s) while living in your previous home?	Text
What percentage of your expendable income (income remaining after housing, taxes, food, and other basic needs) did you use on medication including over-the-counter and prescription medication while living in your previous home?	Number
Did you visit a doctor while living in your previous home?	Text
How many times did you go to the emergency room in your previous home?	Number
How many times did you need an ambulance in your previous home?	Number
Do you currently have health/medical insurance?	Text
Did you purchase health insurance through Healthcare.gov or The Affordable Care Act?	Text
	Text

Table 2 Continued

Do you suffer from asthma or other respiratory conditions in your current home (bronchitis, pneumonia or lung disease)?	
Do you suffer from any other medical condition(s) in your current home?	Text
Have the medical condition(s) changed while you have been living in your current home?	Text
Do you take any medication (including over-the-counter and/or prescription medication) for your medical condition(s) in your current home?	Text
What percentage of your expendable income (income remaining after housing, taxes, food, and other basic needs) do you use on medication including over-the-counter and prescription medication while in your current home?	Text
Have you visited a doctor in the past 12 months?	Text
How many times did you go to the emergency room in the past 12 months?	Number
How many times did you need an ambulance in the past 12 months?	Number

The survey data exported to excel had all the data listed above, most of it was found to be statistically insignificant for this study. The data contained the information about residents' previous house and current one along with their health information. By data cleaning, the final data left is regarding the behavior of residents' in their current house and other factors which are statistically significant and affecting the behavior of the residents like out-side temperature, their health condition and so on. The previous house data of current residents have been cleaned. As this study is related to energy consumption, and previous house data did not have the energy consumption data related to other data which was collected.

For making analysis easier to understand, “Yes” and “No” responses have been converted to “1” and “0” respectively.

Variables like “To increase comfort in your current home, do you open windows at any point during the year?” had 4 different observations. This was converted into one variable named as “open window” with binary observation to make this analysis more feasible.

All the months are matched with seasons and new variable column was created and named as “Season”. Considering Months-January, February and March as winter; April, May and June as spring; July, August and September as summer; October, November and December as fall.

3.3.2 After cleaning

Table 3 Data set after cleaning

ATTRIBUTE	DATA SET
Resident age?	Number
Duration of stay	Number
Affordable knowledge	Binary
Green building knowledge	Binary
Bedrooms	Number

Table 3 Continued

Bathrooms	Number
Usage of Oven/Range	Binary
Usage of Refrigerator	Binary
Usage of Dishwasher	Binary
I Usage of n-Unit Laundry	Binary
Open windows for comforts	Binary
Space Heater for comforts	Binary
Fan for comfort	Binary
Dehumidifier for comfort	Binary
Humidifier for comfort	Binary
Experience- indoor noise	Text
Experience-outdoor noise	Text
Asthma/respiratory conditions	Text
Do you suffer from any other medical condition(s) in your current home?	Binary
KWH	Number
Month	Number
Season	Text
Set Temp	Number
Temperature	Number

3.4 Data analysis

Statistical Analysis

Using XL-STAT (software tool used in data analysis), several test statistics procedures were performed to understand the relationship between residents' behavior and energy consumption.

3.4.1 Impact of indoor and outdoor temperature on energy consumption:

In the first part of the analysis, the independent variable (Y) is energy consumption and explanatory variables (X) are temperature, which is a quantitative variable, and temperature set by resident in their thermostats, which is categorical (qualitative).

Refer Appendix A and A1

The VIF indicate that the independent variables are not highly correlated with one another. This is another evidence of the goodness of the model.

Similarly, the p-value of the model is < 0.0001.

This test was conducted to see if energy consumption is correlated with the thermostat settings (indoor temperature) and outdoor temperature (determined by the weather). The results of the test are as follows:

Refer Appendix B and B1

The adjusted R^2 is just 4%, indicating that only 4% of variation in the data is explained by thermostat settings (indoor temperature).

The P- value is less than 0.05 for indoor temperature 68 and below, and for 69-72. This indicates that the thermostat settings are a significant predictor of energy consumption. While one of the thermostat setting variables (73-75) has a coefficient that is insignificant (p-value>0.05), this is probably happening because we do not have a large enough data set. This helps us conclude that the null hypothesis – that thermostat settings do not affect consumption – can be rejected. Hence as expected, thermostat settings are a significant predictor of energy consumption. The coefficients indicate that setting the thermostat to below 68 degrees' causes' reduction in consumption by approximately 112 kWh as compared to setting of 76 degrees and above. Similarly, consumption when the thermostat is set between 69 and 72 degrees is less by approximately 148 kWh than when the setting is at above 76 degrees. Comparing the values of the coefficients, we can conclude that the most efficient thermostat settings with respect to energy consumption is 69-72 degrees.

However, the P-value associated with outdoor temperature is greater than 0.05. Hence, we cannot reject the null, that is, we do not have enough evidence to conclude that outdoor temperature is a significant predictor of consumption.

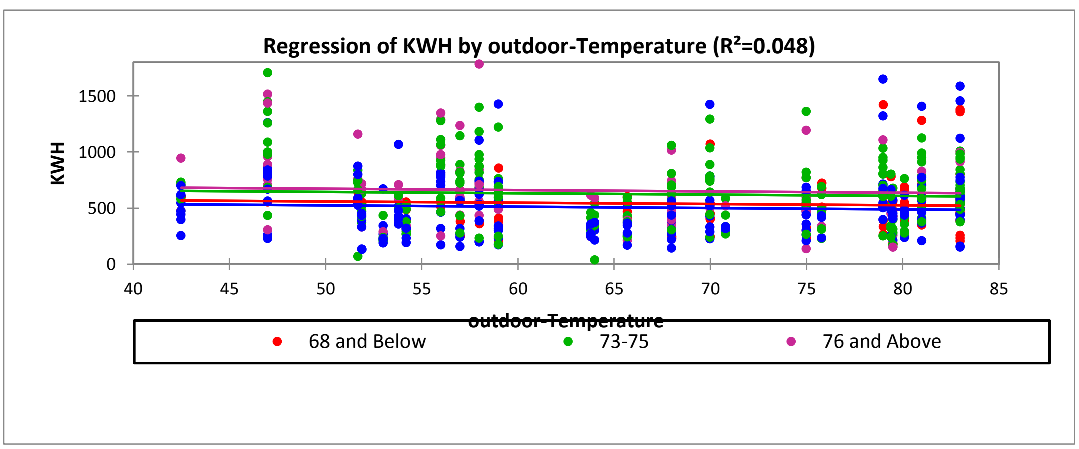


Figure 3 Regression of KWH by outdoor-Temperature of part 1 data set

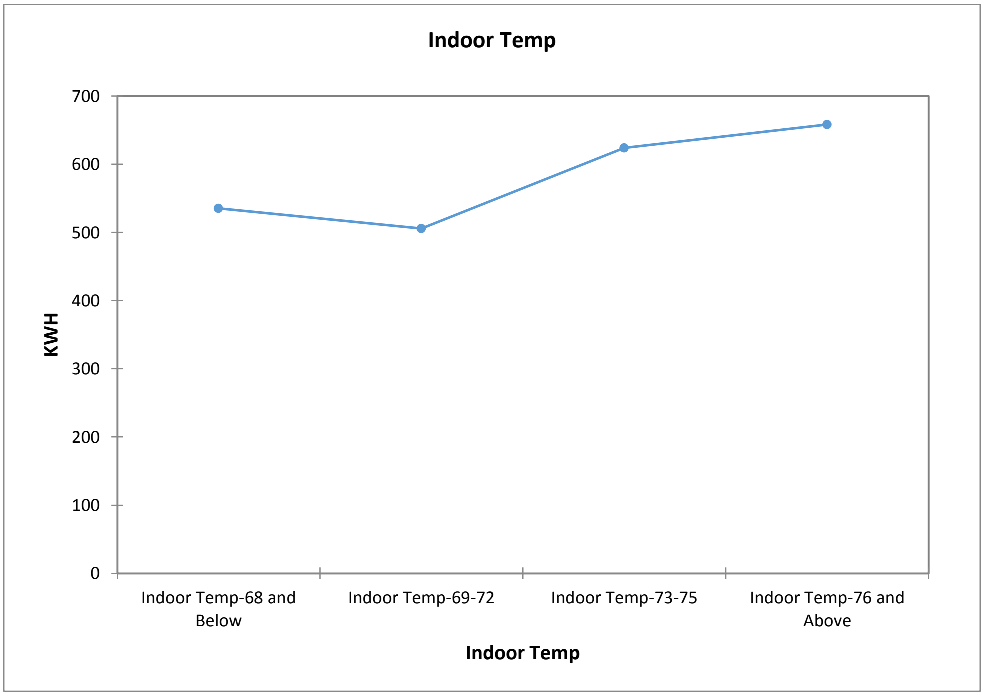


Figure 4 Graph showing KWH in Y-axis and Indoor set temperature in Y-axis in part 1 data set

In the above two graphs, with the increase in indoor set temperature, there is a decrease in energy consumption from Indoor Set Temperature 68 and below to indoor set temperature 69-72. Later, there is a continuous increase in energy consumption from indoor set temperature 69-72 to indoor set temperature 76 and above. This graph also proves that the best indoor temperature setting for reducing energy consumption is 69-72 degrees.

3.4.2 Impact of residents' behavior and awareness on energy consumption:

This test was conducted to see if there is a direct relation between residents' behavior, knowledge/ awareness on green building, knowledge on affordability in housing industry and energy consumption.

In this part of the analysis, the independent variable (Y) is energy consumption and explanatory variables (X) are temperature, which is a quantitative variable, and variables which measures awareness, behavioral variables related to residents are categorical (qualitative) as shown in the table below.

All these variables have binary response value.

The VIF indicate that the independent variables are moderately correlated with one another ($1 < VIF < 5$). This is another evidence of the goodness of the model.

Similarly, the p-value of the model is < 0.0001.

Refer Appendix C

The results of the test are as follows:

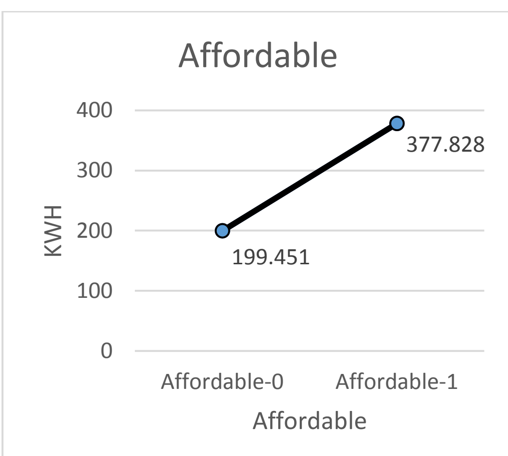
Refer Appendix C1and C2

The adjusted R^2 is just 10%, indicating that only 10% of variation in the data is explained by this study.

The P- value is less than 0.05 for residents' knowledge, residents' behavior and for appliances used by residents like in-unit laundry and space heater and even for opening the windows (Shown in the Figure number 6). This indicates that all residents' knowledge, residents' behavior and appliances used by residents like in-unit laundry and space heater are a significant predictors of energy consumption. While other appliances like fan, dehumidifier, humidifier and oven/range have a coefficient that are insignificant (p-value>0.05), this is probably happening because we do not have a large enough data set. Hence, we do not have enough evidence to prove that the presence of fan, dehumidifier, humidifier and oven/range are significant predictors of energy consumption. Hence, we cannot reject the null, that is, we do not have enough evidence to conclude that these appliances are significant predictors of consumption.

This helps us conclude that the null hypothesis – that behavior characteristics along with appliance used by residents do not affect consumption – can be rejected.

Hence we conclude that residents' knowledge, residents' behavior and for appliances used by residents like in-unit laundry and space heater are a significant predictor of energy consumption. The coefficients indicate that those who do not use space heaters consume 145.564 Kwh more energy than those who use them. Similarly, those who don't know if their apartment is affordable housing and green building consume more energy 178.377 Kwh and 136.112Kwh respectively, than those who have no knowledge about it. This is presented in the graphs below.



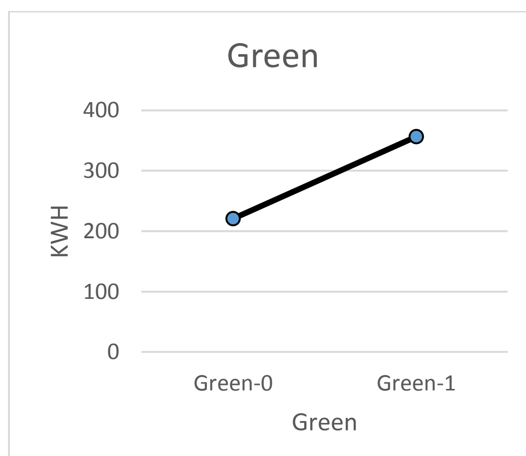
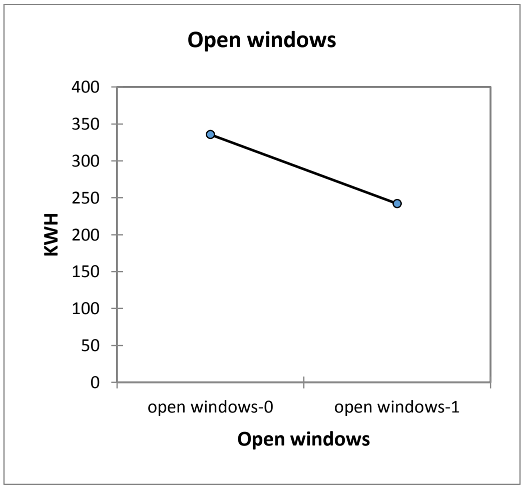


Figure 5 Graph showing KWH in Y-axis and knowledge based on Affordability and Sustainability in X-axis

The graphs above show that the binary value '0' has less energy consumption than binary '1' in both affordable and sustainable (green).



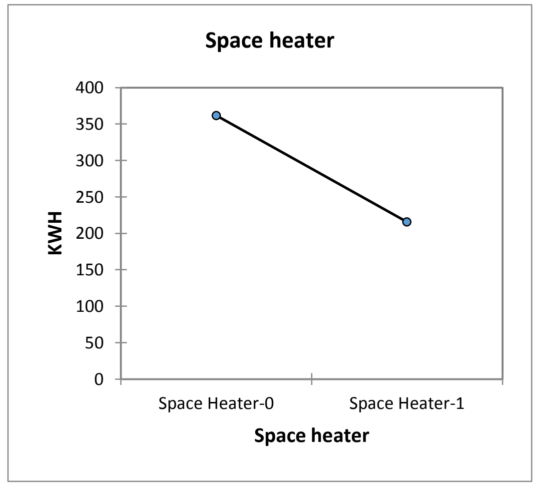


Figure 6 Graph showing KWH in Y-axis and behavior based on opening windows and using space heaters in X-axis

The above graphs "open windows" and "space heater" shows that energy consumption in KWH for binary value '0' is more compared to binary value '1'.

3.4.3 Impact of all variables in the study on energy consumption (I):

This test was conducted to see if there is a direct connection between (energy consumption)^2 and all other variables when the regression with all variables together. To see if there is a better fit model which explains more of a variation, so I transformed the dependent variable into its square and ran the regression based on this transformation. This regression gave better variation in the data compared to above two regression models. Which is explained in detail below.

In this part of the analysis, the independent variable (Y) is (energy consumption) ^{2} in (KWH) ^{2} explanatory variables (X) are out-door temperature and number of bedrooms and bathrooms, which is a quantitative variable and rest of the variables as shown in the table below are categorical (qualitative).

Refer Appendix D

The VIF indicate that the independent variables are moderately correlated with one another (1 < VIF < 5) other than out-door temperature, which has VIF value 91.7. This is another evidence of the goodness of the model.

Similarly, the p-value of the model is < 0.0001.

The results of the test are as follows:

Refer Appendix D1and D2

The adjusted R^2 is 34.9%, indicating that 34.9% of variation in the data is explained by this study.

The P- value is less than 0.05 for 18 variance characteristics. This indicates that there is significant predictor of energy consumption in this results. While majority of them has a coefficient that is insignificant (p-value>0.05), this is probably happening because we do not have a large enough data set. This helps us conclude that the null hypothesis – that behavior characteristics along with other characteristics do not affect consumption – can be rejected.

However, the P-value associated with many of the sources above which are not marked has less than 0.05. Hence, we cannot reject the null, that is, we do not have enough evidence to conclude that these sources are significant predictors of consumption.

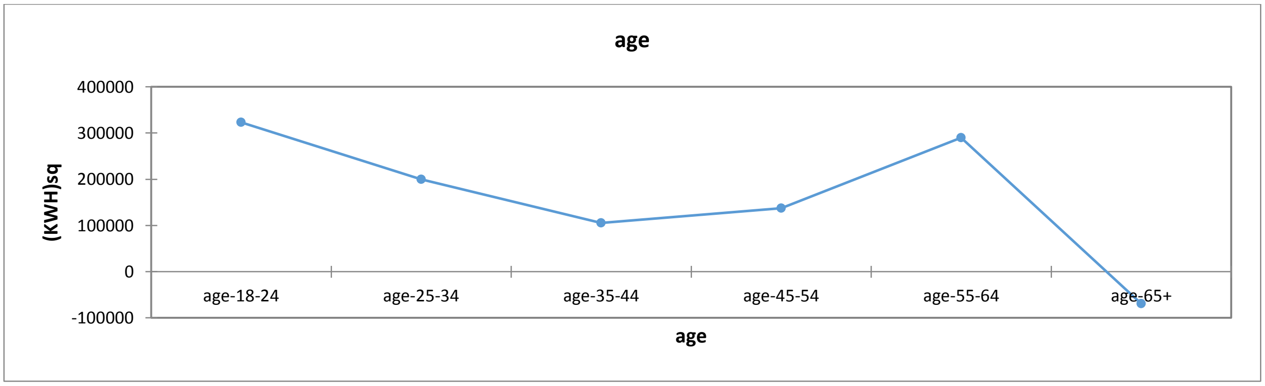


Figure 7 Graph showing (KWH) sq. in Y-axis and age of residents in X-axis of part 3 data set

The above graph about age affecting energy consumption shows that people of age group 18-24 consume more energy and people of age group 65 and above consume less energy. This can be understood that aged people are more concerned about energy consumption than millennials. The reason for this might be because millennials use more energy driven appliances than baby boomers. But, this does not justify the results completely, as the p-value of age group 18-24 in more than 0.05. At the same time the p-value of age group 65+ is less than 0.05. This indicates that there is significant predictor of energy consumption in this results.

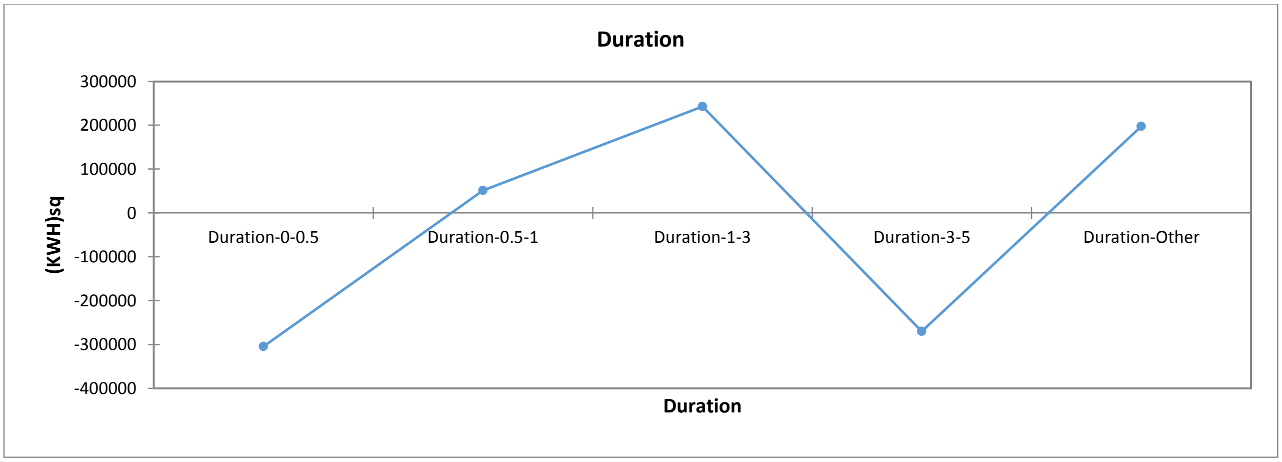


Figure 8 Graph showing (KWH) sq. in Y-axis and duration of stay in X-axis of part 3 data set

The above graph shows that effect of residents' duration of stay for energy consumption. The p-value for residents' duration of stay is more than 0.05. This indicates that there is no significant predictor of energy consumption in this results.

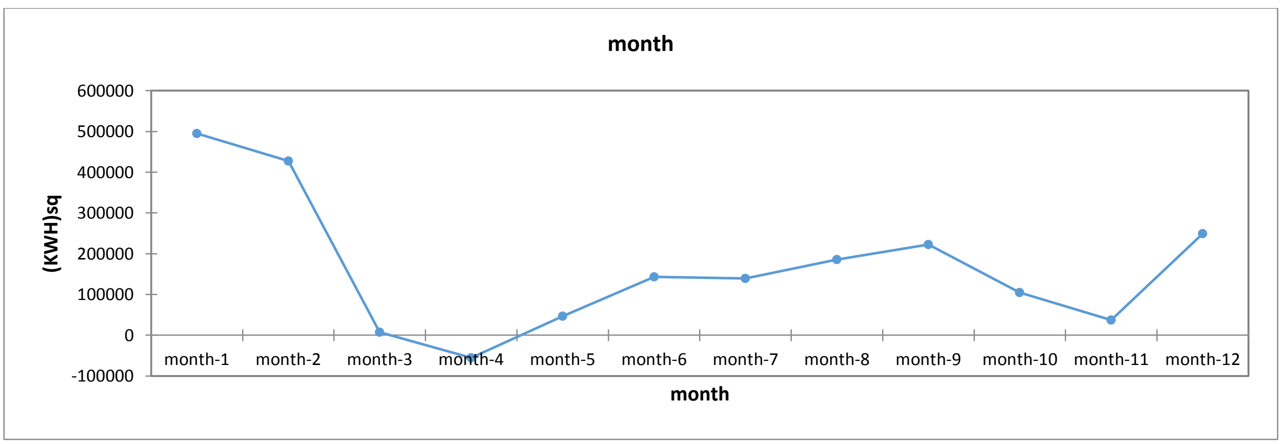


Figure 9 Graph showing (KWH) sq. in Y-axis and month of energy consumption in X-axis of part 3 data set

In the above graph, for the month of January, the energy consumption is high compared to all other months and the least energy consumed is the month of April. To indicate that these are significant predictor of energy consumption in this results, the p-value for both the months are less than 0.05.

3.4.4 Impact of all variables in the study on energy consumption (II):

This study was conducted to see the direct relationship between energy consumption and all other variables.

In this analysis, the independent variable (Y) is energy consumption and explanatory variables (X) are out-door temperature and number of bedrooms and bathrooms, which is a quantitative and qualitative variables include all other variables.

The VIF indicate that the independent variables are moderately correlated with one another ($1 < VIF < 5$) other than bedrooms and bathrooms, which has VIF values 8.467 and 10.498 respectively. This is another evidence of the goodness of the model.

Similarly, the p-value of the model is < 0.0001.

The results of the following regression are as follows:

Refer Appendix E and E1

The adjusted R^2 is 36%, indicating that 36% of variation in the data is explained by this study.

The P- value is less than 0.05 for 12 variance source. This indicates that there are significant predictor of energy consumption in this results. While majority of them has a coefficient that is insignificant (p-value>0.05), this is probably happening because we do not have a large enough data set. This helps us conclude that the null hypothesis – that behavior characteristics along with other characteristics do not affect consumption – can be rejected.

We can also observe that the p-value for all the seasons are less than 0.05. This shows that seasons are a significant predictor of energy consumption.

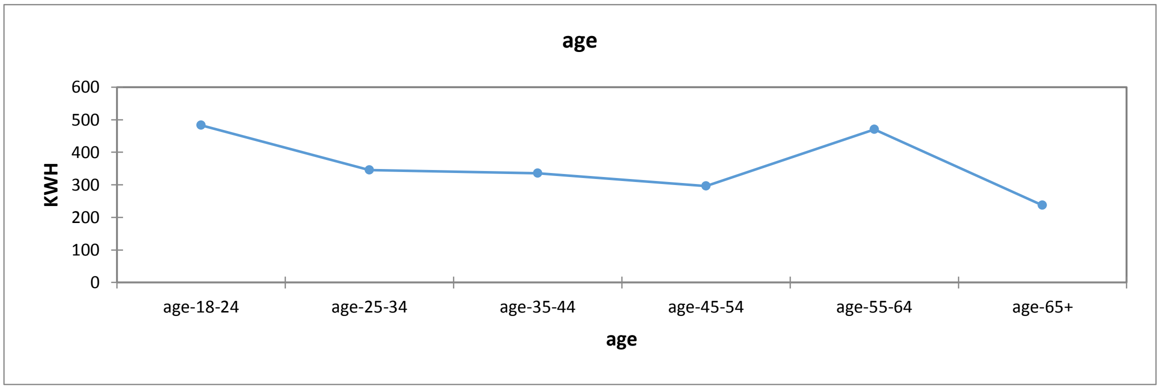


Figure 10 Graph showing KWH in Y-axis and age of residents in X-axis of part 4 data set

In the above graph, one can see that energy consumption for age-group 55-64 is larger compared to other age groups. The p-value also shows that it is the significant predictor of energy consumption. But to compare with other age-group, the p-value of other age-group does not prove the same.

We can also notice that the age group effect on energy consumption also changes with behavior characteristics and various other factors are introduced in a different way in the study.

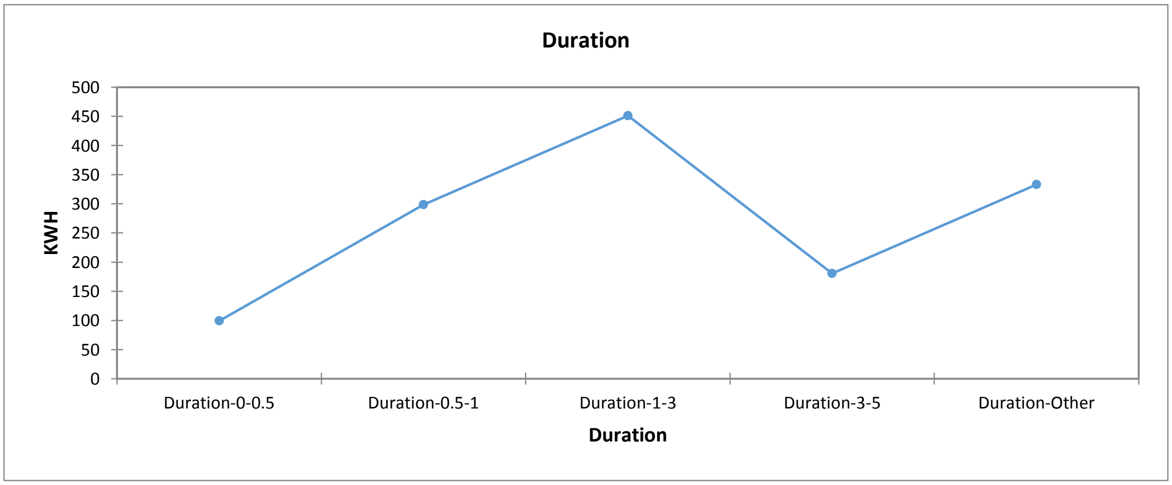


Figure 11 Graph showing KWH in Y-axis and duration of stay in X-axis of part 4 data set

In the above graph, even though the variables are changed while doing different study, the residents' duration of stay does not show that it is a significant predictor of energy consumption.

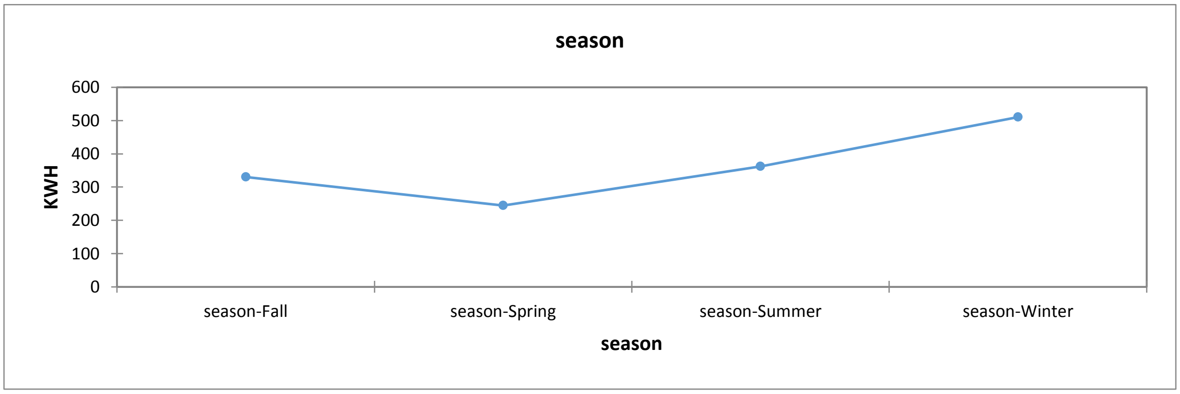


Figure 12 Graph showing KWH in Y-axis and season of energy consumption in X-axis of part 4 data set

In the above graph, the p-value of all seasons are less than 0.05, indicating that they are all a significant predictors of energy consumption. So, we can conclude by showing that the energy consumption is least in spring and maximum in winter.

3.4.5 Impact of all variables in the study on energy consumption (III):

This analysis is similar to the previous one, which was analyzed to see if there is any relationship between all the variables and energy consumption. The only difference in this analysis is that some of the variables have been removed which has no effect or all the answers in that particular variable is same and does not affect the energy consumption.

In this analysis, the independent variable (Y) is energy consumption and explanatory variables (X) are in the form of quantitative and qualitative. Out-door temperature and number of bedrooms and bathrooms, are quantitative variables, and in qualitative variables, all other variables are included.

The VIF indicate that the independent variables are moderately correlated with one another ($1 < VIF < 5$). VIF for bedrooms, bathrooms and temperatures have high correlation with other independent variables. Hence we cannot use this value.

This is another evidence of the goodness of the model.

Similarly, the p-value of the model is < 0.0001.

The results of the following regression is as follows:

Refer Appendix F, F1, F2 and F3

The adjusted R^2 is 37.4%, indicating that 37.4% of variation in the data is explained by this study.

The P- value is less than 0.05 for 15 variance source. This indicates that there are significant predictor of energy consumption in this results. But, as we have mentioned earlier, the VIF value for bedrooms and bathrooms are highly correlated. Hence we have to remove them from the 15 p-value list.

Majority of variance source have a coefficient that is insignificant (p-value>0.05), this is probably happening because we do not have a large variety data set. This helps us conclude that the null hypothesis – that behavior characteristics along with other characteristics do not affect consumption – has been disproved.

Graphs:

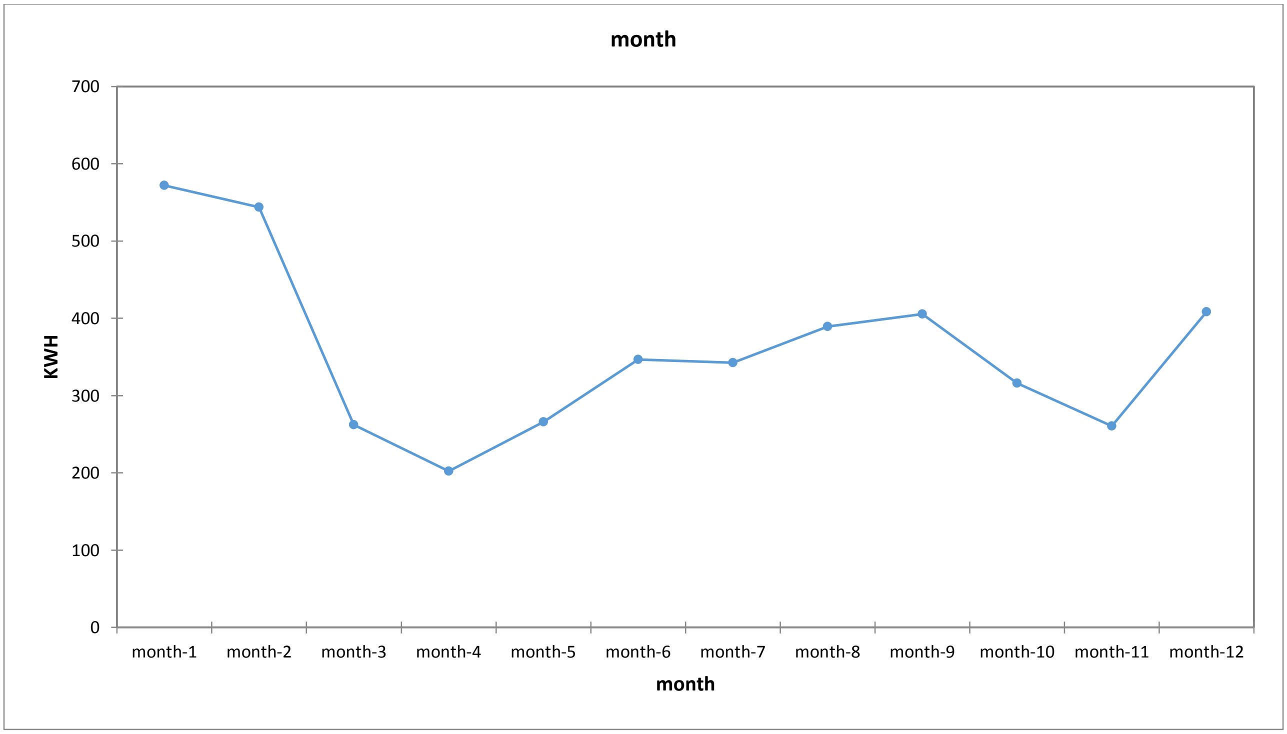


Figure 13 graph showing KWH in Y-axis and Month of energy consumed in X-axis

In the above graph, we can see that the energy consumption for the month of January is higher compared to other months and the energy consumption is low for the month of April. To support this, the p-value for both the months are less than 0.05, hence this indicates that these are significant predictors of energy consumption in this results.

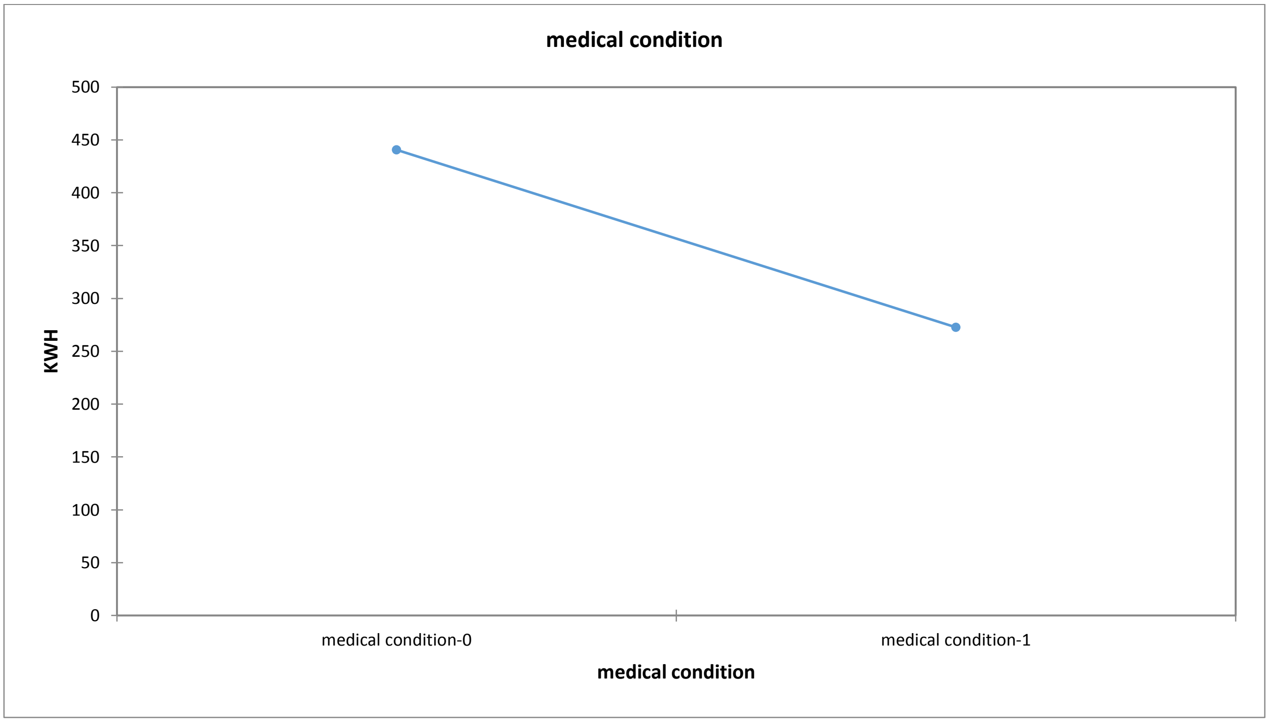


Figure 14 Graph showing KWH in Y-axis and medical condition of residents in X-axis

In the above graph we can see the energy consumption related to residents' health condition. But the p-value for this variable is more than 0.05, thus this indicates that it is not a significant predictor of energy consumption in this results.

CHAPTER 4. CONCLUSION

This study was done understand the effect of thermostat setting and occupant actions of either opening or closing the windows effect on energy consumption among the moderately low income renters.

The first test was conducted to see if energy consumption is correlated with the thermostat settings (indoor temperature) and outdoor temperature (determined by the weather) alone.

The P- value is less than 0.05 for indoor temperature 68 and below, and for 69-72. This indicates that the thermostat settings are a significant predictor of energy consumption. While one of the thermostat setting variables (73-75) has a coefficient that is insignificant (p-value>0.05), this is probably happening because we do not have a large enough data set. This helps us conclude that the null hypothesis – that thermostat settings do not affect consumption – can be rejected. Hence we conclude that thermostat settings are a significant predictor of energy consumption. The coefficients indicate that setting the thermostat to below 68 degrees' causes' reduction in consumption by approximately 112 kWh as compared to setting of 76 degrees and above. Similarly, consumption when the thermostat is set between 69 and 72 degrees is less by approximately 148 kWh than when the setting is at above 76 degrees. Comparing the values of the coefficients, we can conclude that the most efficient thermostat settings with respect to energy consumption is 69-72 degrees.

However, the P-value associated with outdoor temperature is greater than 0.05. Hence, we cannot reject the null, that is, we do not have enough evidence to conclude that outdoor temperature is a significant predictor of consumption.

This shows that the residents' setting the thermostat have significant effect on energy consumption. Proving the hypothesis.

To add to the previous analysis, next analysis was conducted to see the Impact of residents' actions and awareness on energy consumption. The P- value is less than 0.05 for residents' knowledge, residents' behavior and for appliances used by residents like in-unit laundry and space heater and even for opening the windows. This indicates that all residents' knowledge, residents' behavior and appliances used by residents like in-unit laundry and space heater are a significant predictors of energy consumption. While other appliances like fan, dehumidifier, humidifier and oven/range have a coefficient that are insignificant (p-value>0.05), this is probably happening because we do not have a large enough data set. Hence, we do not have enough evidence to prove that the presence of fan, dehumidifier, humidifier and oven/range are significant predictors of energy consumption. Hence, one cannot reject the null, that is, we do not have enough evidence to conclude that these appliances are significant predictors of consumption.

This conclusion is a null hypothesis – that actions along with appliance used by residents do not affect consumption – can be rejected.

Hence we conclude that residents' knowledge, residents' actions and appliances used by residents like in-unit laundry and space heater are a significant predictor of energy consumption. The coefficients indicate that those who do not use space heaters consume 145.564 Kwh more energy than those who use them. Similarly, those who know if their apartment is affordable housing and green building consume less energy 178.377 Kwh and 136.112Kwh respectively, than those who have no knowledge about it.

In the third part of the regression, the test was conducted to see if there is a direct connection between (energy consumption) ^{2} and all other variables when the regression with all variables together. To see if there is a better fit model which explains more of a variation, so I transformed the dependent variable into its square and ran the regression based on this transformation. This regression explained more variation in the data compared to first two regression models but compared to last two regressions, this value was slightly less.

The P- value is less than 0.05 for 18 variance characteristics. This indicates that there is significant predictor of energy consumption in this results. While majority of them has a coefficient that is insignificant (p-value>0.05), this is probably happening because we do not have a large enough data set. This helps us conclude that the null hypothesis – that behavior characteristics along with other characteristics do not affect consumption – can be rejected.

However, the P-value associated with many of the sources was less than 0.05. Hence, we cannot reject the null, that is, we do not have enough evidence to conclude that these sources are significant predictors of consumption.

Last two regression study was conducted to see the direct relationship between energy consumption and all other variables. The only difference being, more cleaned data for the last regression.

The adjusted R^2 is 36% and 37% respectively, indicating that 36% and 37% of variation in the data is explained by the two studies.

The P- value is less than 0.05 for many variance source. This indicates that there is significant predictor of energy consumption in this results. While majority of them has a coefficient that is insignificant (p-value>0.05).

This helps to conclude that the null hypothesis – that behavior characteristics along with other characteristics do not affect consumption – can be rejected.

Observations suggest that the p-value for all the seasons are less than 0.05. This shows that seasons are a significant predictor of energy consumption.

This shows that the residents' setting the thermostat have significant effect on energy consumption. Proving the hypothesis. Here, human behavior is defined as the temperature that residents set their indoor thermostats to and whether or not the residents open their windows in different seasons." Has been proved.

CHAPTER 5. RECOMMENDATION FOR FUTURE RESEARCH

1. Develop programs to educate or create awareness among people about green buildings to reduce energy consumption. By telling about the benefits like tax credits, rebates which are linked with green building, more communities are attracted in adopting such ratings.
2. Advocate the installation of Smart homes devices which will help in tracking energy consumption in each of the appliances used. This will make people more aware of the power consumed by each of the appliances they use on daily/ weekly basis.
3. Policies/ research supporting energy conservation methods can be made to make people more aware of energy conservation in their community/ apartments. Policies which gives rebates for apartments/ community which perform better and implements methods to save energy should be encouraged.
4. Community manager's involvement is very important factor in influencing energy consumption and also in making their residents more aware of energy consumption. Communities can get involved in giving periodic notice to help residents understand their energy usage and tell them about energy saving techniques. Proper periodic maintenance of appliances will also help in reducing energy consumption. If the community employees/managers are more involved in the energy improvement activities, the community will perform better than before.

APPENDICES

APPENDIX A

Table 4 Variable, Categories, Frequency and percentage of part 1 data set

Variable	Categories	Frequencies	%
Indoor Temp	68 and Below	83	14.310
	69-72	197	33.966
	73-75	212	36.552
	76 and Above	88	15.172

APPENDIX A1

Table 5 Multicollinearity statistics of part 1 data set

Statistic	outdoor-Temperature	Indoor Temp-68 and Below	Indoor Temp-69-72	Indoor Temp-73-75	Indoor Temp-76 and Above
Tolerance	0.952	0.970	0.998	0.999	0.976
VIF	1.050	1.031	1.002	1.001	1.024

APPENDIX B

Table 6 Model parameters of part 1 data set

Source	Value	Standard error	T	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	729.353	67.707	10.772	< 0.0001	596.370	862.335
outdoor-Temperature	-1.153	0.982	-1.175	0.240	-3.082	0.775
Indoor Temp-68 and Below	-111.579	44.400	-2.513	0.012	-198.786	-24.373
Indoor Temp-69-72	-148.223	36.533	-4.057	< 0.0001	-219.978	-76.468
Indoor Temp-73-75	-28.510	36.278	-0.786	0.432	-99.763	42.743
Indoor Temp-76 and Above	0.000	0.000				

APPENDIX B1

Table 7 Goodness of fit statistics of part 1 data set

	Value
R^2	0.048
Adjusted R^2	0.041

APPENDIX C

Table 8 Variable, Categories, Frequency and percentage of part 2 data set

Variable	Categories	Frequencies	%
Affordable	0	11	1.852
	1	583	98.148
Green	0	126	21.212
	1	468	78.788
Oven/Range	0	14	2.357
	1	580	97.643
Refrigerator	1	594	100.000
Dishwasher	1	594	100.000
In-Unit Laundry	0	84	14.141
	1	510	85.859
open windows	0	402	67.677
	1	192	32.323
Space Heater	0	529	89.057
	1	65	10.943
Fan	0	129	21.717
	1	465	78.283
Dehumidifier	0	569	95.791
	1	25	4.209
Humidifier	0	505	85.017
	1	89	14.983

APPENDIX C1

Table 9 Model parameters of part 2 data set

Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	422.932	60.849	6.951	< 0.0001	303.423	542.441
Affordable-0	-178.377	87.687	-2.034	0.042	-350.598	-6.156
Affordable-1	0.000	0.000				
Green-0	-136.112	31.071	-4.381	< 0.0001	-197.136	-75.088
Green-1	0.000	0.000				
Oven/Range-0	-97.430	87.227	-1.117	0.264	-268.746	73.886

Table 9 Continued

Oven/Range-1	0.000	0.000				
Refrigerator-1	0.000	0.000				
Dishwasher-1	0.000	0.000				
In-Unit Laundry-0	-92.537	38.217	-2.421	0.016	-167.597	-17.477
In-Unit Laundry-1	0.000	0.000				
open windows-0	93.457	25.050	3.731	0.000	44.259	142.655
open windows-1	0.000	0.000				
Space Heater-0	145.564	39.255	3.708	0.000	68.465	222.662
Space Heater-1	0.000	0.000				
Fan-0	0.462	27.938	0.017	0.987	-54.408	55.333
Fan-1	0.000	0.000				
Dehumidifier-0	42.395	63.147	0.671	0.502	-81.628	166.418
Dehumidifier-1	0.000	0.000				
Humidifier-0	-46.007	34.177	-1.346	0.179	-113.133	21.119
Humidifier-1	0.000	0.000				

APPENDIX C2

Table 10 Goodness of fit statistics of part 1 data set

	Value
R^2	0.116
Adjusted R^2	0.102

APPENDIX D

Table 11 Variable, Categories, Frequency and percentage of part 3 data set

Variable	Categories	Frequencies	%
age	18-24	60	10.067
	25-34	97	16.275
	35-44	131	21.980
	45-54	50	8.389
	55-64	22	3.691
	65+	236	39.597
Duration	0-0.5	22	3.691
	0.5-1	49	8.221
	1-3	476	79.866
	3-5	35	5.872
	Other	14	2.349
Affordable	0	11	1.846
	1	585	98.154
Green	0	126	21.141
	1	470	78.859
Oven/Range	0	14	2.349
	1	582	97.651
Refrigerator	1	596	100.000
Dishwasher	1	596	100.000
In-Unit Laundry	0	85	14.262
	1	511	85.738
open windows	0	403	67.617
	1	193	32.383
Space Heater	0	531	89.094
	1	65	10.906
Fan	0	130	21.812
	1	466	78.188
Dehumidifier	0	571	95.805
	1	25	4.195
Humidifier	0	507	85.067
	1	89	14.933
indoor noise	I Always Hear My Neighbors Through the Walls and/or Floors	180	30.201
	I Never Hear My Neighbors Through the Walls and/or Floors	126	21.141
	I Rarely Hear My Neighbors Through the Walls and/or Floors	165	27.685

Table 11 Continued

	I Sometimes Hear My Neighbors Through the Walls and/or Floors	125	20.973
outdoor noise	I Always Hear Noise From Outside	141	23.658
	I Never Hear Noise From Outside	50	8.389
	I Rarely Hear Noise From Outside	234	39.262
	I Sometimes Hear Noise From Outside	171	28.691
asthma or other respiratory	Asthma	35	5.872
	Asthma and Other Respiratory Conditions	34	5.705
	I Do Not Suffer From Asthma or Other Respiratory Conditions	413	69.295
	Other Respiratory Conditions but Not Asthma	114	19.128
medical condition	0	287	48.154
	1	309	51.846
month	1	49	8.221
	2	49	8.221
	3	59	9.899
	4	57	9.564
	5	41	6.879
	6	47	7.886
	7	49	8.221
	8	49	8.221
	9	49	8.221
	10	49	8.221
	11	49	8.221
	12	49	8.221
season	Fall	147	24.664
	Spring	157	26.342
	Summer	145	24.329
	Winter	147	24.664
Indoor Temp	68 and Below	83	13.926
	69-72	198	33.221
	73-75	212	35.570
	76 and Above	89	14.933
	N/A (I Have Not Lived in My Current Home During Summer)	6	1.007
	N/A (I Have Not Lived in My Current Home During Winter)	8	1.342

APPENDIX D1

Table 12 Model parameters of part 3 data set

Source	Value	Standard error	t	Pr > |t|
Intercept	-791068.113	635924.578	-1.244	0.214
outdoor-Temperature	16222.717	11554.877	1.404	0.161
# of Bedrooms	133259.051	64080.054	2.080	0.038
# of Bathrooms	313304.084	102303.000	3.063	0.002
age-18-24	6694.914	107769.675	0.062	0.950
age-25-34	-8775.394	97736.563	-0.090	0.928
age-35-44	-146601.865	70303.410	-2.085	0.038
age-45-54	74310.774	85285.707	0.871	0.384
age-55-64	481424.312	144286.415	3.337	0.001
age-65+	0.000	0.000		
Duration-0-0.5	-504704.235	283331.476	-1.781	0.075
Duration-0.5-1	-405436.055	235556.405	-1.721	0.086
Duration-1-3	-301275.227	224579.750	-1.342	0.180
Duration-3-5	-469605.784	303583.290	-1.547	0.122
Duration-Other	0.000	0.000		
Affordable-0	-233932.112	146097.911	-1.601	0.110
Affordable-1	0.000	0.000		
Green-0	-113778.125	76441.439	-1.488	0.137
Green-1	0.000	0.000		
Oven/Range-0	0.000	0.000		
Oven/Range-1	0.000	0.000		
Refrigerator-1	0.000	0.000		
Dishwasher-1	0.000	0.000		
In-Unit Laundry-0	-255686.028	72167.263	-3.543	0.000
In-Unit Laundry-1	0.000	0.000		
open windows-0	-53763.466	41984.347	-1.281	0.201
open windows-1	0.000	0.000		
Space Heater-0	-296390.551	102754.919	-2.884	0.004
Space Heater-1	0.000	0.000		

Table 12 Continued

Fan-0	-164606.217	60904.501	-2.703	0.007
Fan-1	0.000	0.000		
Dehumidifier-0	314326.451	164959.788	1.905	0.057
Dehumidifier-1	0.000	0.000		
Humidifier-0	126000.150	75650.908	1.666	0.096
Humidifier-1	0.000	0.000		
indoor noise-I Always Hear My Neighbors Through the Walls and/or Floors	-172170.399	83271.010	-2.068	0.039
indoor noise-I Never Hear My Neighbors Through the Walls and/or Floors	136588.775	122899.640	1.111	0.267
indoor noise-I Rarely Hear My Neighbors Through the Walls and/or Floors	-19871.908	90939.875	-0.219	0.827
indoor noise-I Sometimes Hear My Neighbors Through the Walls and/or Floors	0.000	0.000		
outdoor noise-I Always Hear Noise From Outside	-171875.316	67621.509	-2.542	0.011
outdoor noise-I Never Hear Noise From Outside	16978.112	87398.267	0.194	0.846
outdoor noise-I Rarely Hear Noise From Outside	2661.139	71346.425	0.037	0.970
outdoor noise-I Sometimes Hear Noise From Outside	0.000	0.000		
asthma or other respiratory-Asthma	176180.763	136886.239	-1.287	0.199
asthma or other respiratory-Asthma and Other Respiratory Conditions	-51103.676	109280.596	-0.468	0.640
asthma or other respiratory-I Do Not Suffer From Asthma or Other Respiratory Conditions	-45772.087	77402.968	-0.591	0.555
asthma or other respiratory-Other Respiratory Conditions but Not Asthma	0.000	0.000		
medical condition-0	192698.745	58809.758	3.277	0.001
medical condition-1	0.000	0.000		
month-1	407663.780	136711.218	2.982	0.003
month-2	195042.471	74098.206	2.632	0.009
month-3	-197895.154	74631.033	-2.652	0.008
month-4	-445658.734	150934.903	-2.953	0.003
month-5	-552212.458	224588.611	-2.459	0.014

Table 12 Continued

month-6	-523192.128	297135.190	-1.761	0.079
month-7	-538780.490	313971.396	-1.716	0.087
month-8	-487352.653	310265.114	-1.571	0.117
month-9	-385683.732	266190.510	-1.449	0.148
month-10	-350111.331	164490.450	-2.128	0.034
month-11	-239112.777	78353.395	-3.052	0.002
month-12	0.000	0.000		
season-Fall	0.000	0.000		
season-Spring	0.000	0.000		
season-Summer	0.000	0.000		
season-Winter	0.000	0.000		
Indoor Temp-68 and Below	56807.429	211498.832	0.269	0.788
Indoor Temp-69-72	-67830.881	198484.539	-0.342	0.733
Indoor Temp-73-75	75301.875	205966.417	0.366	0.715
Indoor Temp-76 and Above	57476.210	204488.858	0.281	0.779
Indoor Temp-N/A (I Have Not Lived in My Current Home During Summer)	297313.187	284965.361	1.043	0.297
Indoor Temp-N/A (I Have Not Lived in My Current Home During Winter)	0.000	0.000		

APPENDIX D2

Table 13 Goodness of fit statistics of part 3 data set

	Value
R^2	0.399
Adjusted R^2	0.349

APPENDIX E

Table 14 Model parameters of part 4 data set

Source	Value	Standard error	t	Pr > |t|
Intercept	363.955	170.952	2.129	0.034
outdoor-Temperature	0.859	1.553	0.553	0.580
# of Bedrooms	90.803	40.525	2.241	0.025
# of Bathrooms	165.859	61.615	2.692	0.007
age-18-24	56.029	68.106	0.823	0.411
age-25-34	-26.877	62.651	-0.429	0.668
age-35-44	-64.058	43.733	-1.465	0.144
age-45-54	6.298	54.791	0.115	0.909
age-55-64	302.695	92.062	3.288	0.001
age-65+	0.000	0.000		
Duration-0-0.5	-234.120	179.973	-1.301	0.194
Duration-0.5-1	-162.400	149.851	-1.084	0.279
Duration-1-3	-56.105	143.399	-0.391	0.696
Duration-3-5	-152.701	192.714	-0.792	0.428
Duration-Other	0.000	0.000		
Affordable-0	-204.941	93.509	-2.192	0.029
Affordable-1	0.000	0.000		
Green-0	-74.684	48.327	-1.545	0.123
Green-1	0.000	0.000		
Oven/Range-0	0.000	0.000		
Oven/Range-1	0.000	0.000		
Refrigerator-1	0.000	0.000		
Dishwasher-1	0.000	0.000		
In-Unit Laundry-0	-171.734	46.199	-3.717	0.000
In-Unit Laundry-1	0.000	0.000		
open windows-0	-18.988	26.906	-0.706	0.481
open windows-1	0.000	0.000		
Space Heater-0	-127.820	65.802	-1.942	0.053
Space Heater-1	0.000	0.000		
Fan-0	-36.012	38.770	-0.929	0.353
Fan-1	0.000	0.000		
Dehumidifier-0	179.741	105.526	1.703	0.089
Dehumidifier-1	0.000	0.000		
Humidifier-0	28.215	48.472	0.582	0.561
Humidifier-1	0.000	0.000		

Table 14 Continued

Indoor noise-I Always Hear My Neighbors Through the Walls and/or Floors	-60.041	52.651	-1.140	0.255
indoor noise-I Never Hear My Neighbors Through the Walls and/or Floors	80.862	78.656	1.028	0.304
indoor noise-I Rarely Hear My Neighbors Through the Walls and/or Floors	-8.969	58.156	-0.154	0.877
indoor noise-I Sometimes Hear My Neighbors Through the Walls and/or Floors	0.000	0.000		
outdoor noise-I Always Hear Noise From Outside	-103.869	42.697	-2.433	0.015
outdoor noise-I Never Hear Noise From Outside	-6.053	55.852	-0.108	0.914
outdoor noise-I Rarely Hear Noise From Outside	-6.897	45.682	-0.151	0.880
outdoor noise-I Sometimes Hear Noise From Outside	0.000	0.000		
asthma or other respiratory-Asthma	-45.721	87.658	-0.522	0.602
asthma or other respiratory-Asthma and Other Respiratory Conditions	44.664	68.924	0.648	0.517
asthma or other respiratory-I Do Not Suffer From Asthma or Other Respiratory Conditions	4.958	49.405	0.100	0.920
asthma or other respiratory-Other Respiratory Conditions but Not Asthma	0.000	0.000		
medical condition-0	89.442	37.441	2.389	0.017
medical condition-1	0.000	0.000		
season-Fall	-194.326	38.998	-4.983	< 0.0001

Table 14 Continued

season-Spring	-266.434	37.182	-7.166	< 0.0001
season-Summer	-176.016	54.674	-3.219	0.001
season-Winter	0.000	0.000		
Indoor Temp-68 and Below	-34.270	134.954	-0.254	0.800
Indoor Temp-69-72	-105.653	126.908	-0.833	0.405
Indoor Temp-73-75	-16.496	131.726	-0.125	0.900
Indoor Temp-76 and Above	-29.173	130.778	-0.223	0.824
Indoor Temp-N/A (I Have Not Lived in My Current Home During Summer)	-22.789	182.394	-0.125	0.901
Indoor Temp-N/A (I Have Not Lived in My Current Home During Winter)	0.000	0.000		

APPENDIX E1

Table 15 Goodness of fit statistics of part 4 data set

	Value
R^2	0.402
Adjusted R^2	0.361

APPENDIX F

Table 16 Summary statistics of quantitative variables of part 5 data set

Variable	Observations	Obs. with missing data	Obs. without missing data	Min	Max	Mean	Std. deviation
KWH	580	0	580	34.000	1783.000	576.252	289.445
# of Bedrooms	580	0	580	1.000	3.000	1.681	0.683
# of Bathrooms	580	0	580	1.000	2.000	1.534	0.499
outdoor-Temperature	580	0	580	42.500	83.000	66.208	12.296

APPENDIX F1

Table 17 Multicollinearity statistics of part 5 data set

Statistic	Tolerance	VIF
# of Bedrooms	0.118	8.478
# of Bathrooms	0.087	11.556
outdoor-Temperature	0.011	89.778
age-18-24	0.378	2.643
age-25-34	0.414	2.415
age-35-44	0.371	2.696
age-45-54	0.624	1.603
age-55-64	0.319	3.135
age-65+	0.314	3.188
Duration-0-0.5	0.574	1.743
Duration-0.5-1	0.587	1.704
Duration-1-3	0.370	2.704
Duration-3-5	0.281	3.558
Affordable-0	0.568	1.762
Affordable-1	0.568	1.762
Green-0	0.238	4.206
Green-1	0.238	4.206
In-Unit Laundry-0	0.377	2.652

Table 17 Continued

In-Unit Laundry-1	0.377	2.652
open windows-0	0.580	1.724
open windows-1	0.580	1.724
Space Heater-0	0.233	4.283
Space Heater-1	0.233	4.283
Fan-0	0.362	2.766
Fan-1	0.362	2.766
Dehumidifier-0	0.201	4.979
Dehumidifier-1	0.201	4.979
Humidifier-0	0.302	3.310
Humidifier-1	0.302	3.310
indoor noise-I Always Hear My Neighbors Through the Walls and/or Floors	0.391	2.554
indoor noise-I Never Hear My Neighbors Through the Walls and/or Floors	0.282	3.543
indoor noise-I Rarely Hear My Neighbors Through the Walls and/or Floors	0.312	3.210
indoor noise-I Sometimes Hear My Neighbors Through the Walls and/or Floors	0.251	3.979
outdoor noise-I Always Hear Noise From Outside	0.460	2.173
outdoor noise-I Never Hear Noise From Outside	0.395	2.533
outdoor noise-I Sometimes Hear Noise From Outside	0.351	2.850
asthma or other respiratory-Asthma	0.335	2.987
asthma or other respiratory-Asthma and Other Respiratory Conditions	0.402	2.489
asthma or other respiratory-I Do Not Suffer From Asthma or Other Respiratory Conditions	0.257	3.898
asthma or other respiratory-Other Respiratory Conditions but Not Asthma	0.268	3.729
medical condition-0	0.260	3.847
medical condition-1	0.260	3.847
month-1	0.631	1.586
month-2	0.710	1.408
month-3	0.482	2.073
month-4	0.683	1.464
month-5	0.621	1.611
month-6	0.731	1.368

Table 17 Continued

month-7	0.720	1.388
month-8	0.721	1.387
month-9	0.488	2.051
month-10	0.726	1.377
month-11	0.462	2.165
month-12	0.694	1.441
Indoor Temp-68 and Below	0.504	1.986
	0.597	1.676
Indoor Temp-73-75	0.420	2.380
Indoor Temp-76 and Above	0.614	1.629

APPENDIX F2

Table 18 Goodness of fit statistics of part 5 data set

	Value
R^2	0.421
Adjusted R^2	0.374

APPENDIX F3

Table 19 Model parameters of part 5 data set

Source	Value	Standard error	t	Pr > |t|
Intercept	-179.881	414.460	-0.434	0.664
# of Bedrooms	96.662	40.589	2.381	0.018
# of Bathrooms	143.527	64.817	2.214	0.027
outdoor-Temperature	8.835	7.335	1.204	0.229
age-18-24	43.716	68.284	0.640	0.522
age-25-34	-30.607	62.151	-0.492	0.623
age-35-44	-74.677	44.610	-1.674	0.095
age-45-54	2.293	54.453	0.042	0.966
age-55-64	292.789	91.556	3.198	0.001
age-65+	0.000	0.000		
Duration-0-0.5	-211.998	179.561	-1.181	0.238
Duration-0.5-1	-145.051	149.253	-0.972	0.332
Duration-1-3	-46.085	142.280	-0.324	0.746

Table 19 Continued

Duration-3-5	-126.866	192.450	-0.659	0.510
Duration-Other	0.000	0.000		
Affordable-0	-206.647	92.556	-2.233	0.026
Affordable-1	0.000	0.000		
Green-0	-66.239	48.452	-1.367	0.172
Green-1	0.000	0.000		
In-Unit Laundry-0	-167.439	45.903	-3.648	0.000
In-Unit Laundry-1	0.000	0.000		
open windows-0	-19.397	26.717	-0.726	0.468
open windows-1	0.000	0.000		
Space Heater-0	-129.539	65.116	-1.989	0.047
Space Heater-1	0.000	0.000		
Fan-0	-41.255	38.695	-1.066	0.287
Fan-1	0.000	0.000		
Dehumidifier-0	174.537	104.500	1.670	0.095
Dehumidifier-1	0.000	0.000		
Humidifier-0	26.984	48.013	0.562	0.574
Humidifier-1	0.000	0.000		
indoor noise-I Always Hear My Neighbors Through the Walls and/or Floors	-68.719	52.766	-1.302	0.193
indoor noise-I Never Hear My Neighbors Through the Walls and/or Floors	73.876	78.060	0.946	0.344
indoor noise-I Rarely Hear My Neighbors Through the Walls and/or Floors	-16.759	57.874	-0.290	0.772
indoor noise-I Sometimes Hear My Neighbors Through the Walls and/or Floors	0.000	0.000		
outdoor noise-I Always Hear Noise From Outside	-93.797	43.118	-2.175	0.030
outdoor noise-I Never Hear Noise From Outside	-9.001	55.358	-0.163	0.871
outdoor noise-I Rarely Hear Noise From Outside	-3.772	45.272	-0.083	0.934
outdoor noise-I Sometimes Hear Noise From Outside	0.000	0.000		
asthma or other respiratory-Asthma	-44.121	86.774	-0.508	0.611
asthma or other respiratory-Asthma and Other Respiratory Conditions	30.145	69.344	0.435	0.664
asthma or other respiratory-I Do Not Suffer From Asthma or Other Respiratory Conditions	-0.095	49.085	-0.002	0.998
asthma or other respiratory-Other Respiratory Conditions but Not Asthma	0.000	0.000		
medical condition-0	94.060	37.311	2.521	0.012
medical condition-1	0.000	0.000		

Table 19 Continued

month-1	251.831	87.064	2.892	0.004
month-2	145.193	47.429	3.061	0.002
month-3	-118.536	48.210	-2.459	0.014
month-4	-284.389	95.938	-2.964	0.003
month-5	-334.037	142.607	-2.342	0.020
month-6	-288.696	188.417	-1.532	0.126
month-7	-299.129	199.241	-1.501	0.134
month-8	-249.401	196.944	-1.266	0.206
month-9	-197.779	168.929	-1.171	0.242
month-10	-203.970	104.514	-1.952	0.052
month-11	-162.535	50.018	-3.250	0.001
month-12	0.000	0.000		
Indoor Temp-68 and Below	-11.190	50.121	-0.223	0.823
Indoor Temp-69-72	-77.191	36.593	-2.109	0.035
Indoor Temp-73-75	12.752	39.316	0.324	0.746
Indoor Temp-76 and Above	0.000	0.000		

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