

## ABSTRACT

Title of Document: VARIATIONS ON THE NORMATIVE  
FEEDBACK MODEL FOR ENERGY EFFICIENT  
BEHAVIOR IN THE CONTEXT OF MILITARY  
FAMILY HOUSING

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In discussions on energy efficiency, the topic often involves the development of a new technology. But models that target human behavior change can also generate significant energy savings, often with less expense. One such model that has been employed to millions of households across the United States is the normative feedback model. This model integrates the most salient research from the field of social norms into the utility billing process. Residents receive a home energy report that compares their energy consumption to the average energy consumption of their neighbors. Resulting behavior changes have led to energy savings of between 1.4% and 3.1% (Alcott, 2011). This research tests three variations of the normative feedback model, with the aim of determining its boundary conditions and improving it. Each variation aligns with one of the three research objectives: 1) to determine whether normative feedback generates significant energy savings when applied to households that are not billed for utility usage, 2) to determine whether increasing the proximity of comparison increases the energy

savings generated by normative feedback, and 3) to determine energy savings associated with the implementation of a normative-based utility billing system.

The first two variations were tested through an experiment conducted at Joint Base Andrews in Maryland, where residents are not currently billed for their utility usage. Residents received normative feedback via home energy reports for three consecutive months. Results were analyzed through both a differences-in-differences analysis and a multiple regression analysis, and an overall energy savings of 3.8% was identified. Thus, the normative feedback model can generate energy savings even in the absence of a billing system and could therefore be employed in the two-thirds of military family housing that are not yet billed for utilities, with resulting savings of approximately \$19.3 million annually.

In the home energy report experiment, residents were compared at three different levels of proximity: neighborhood, street, and next-door neighbor. The analysis identified an energy savings of 3.8% at the neighborhood level, 4.9% at the street level, and 2.8% at the next-door neighbor level. These results indicate a “sweet spot” in setting the proximity level of comparisons. By increasing the proximity from the neighborhood to the street level, energy savings increased, which is consistent with expectations based on a previous study in a different context (Goldstein, Cialdini, & Griskevicius, 2008). But increasing the proximity further to the next-door neighbor level actually reduced the energy savings. Therefore, to maximize effectiveness, future applications of normative feedback for energy efficiency should make comparisons at the street level of proximity.

And finally, this research investigated the use of normative feedback as the basis for a utility billing system. Such a system, as implemented at Fort Belvoir in Virginia, establishes a monthly baseline equal to the average energy consumption for that month. Residents make payments for their consumption over the baseline and receive payments for their consumption under the baseline. A multiple regression analysis found that the implementation of this billing system into a community not previously billed for utility usage generated an energy savings of 14.1%. This result takes an important first step towards the development of a billing program optimization model for the military's transition to utility billing.

Variations on the Normative Feedback Model for  
Energy Efficient Behavior in  
the Context of Military Family Housing

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# Chapter 1: Introduction

## 1.1 Background

Whether the discussion is climate change, the increasing cost of energy or dependence on foreign oil, reducing energy consumption is consistently recognized as an objective of high importance. The residential sector, accounting for 23% of the total energy consumption in the United States (Energy Information Administration, 2011), has often been the target of new energy efficient technology. Yet, for all the technological advancements in household energy efficiency, technology alone cannot obtain the full potential of energy savings. The residents themselves must decide to adopt the new technology, employ it correctly and, perhaps most significantly, adjust their lifestyles and behaviors. Some studies estimate that changed behaviors alone might reduce household energy consumption in the United States by roughly 25% (Gardner & Stern, 2008) (Laitner, Ehrhardt-Martinez, & McKinney, 2009). So, determining and improving upon the best methods for influencing residential energy consumption behaviors can go a long way in reducing energy consumption.

Many different approaches exist to encourage energy conservation, such as rewards and role models, but one approach in particular has gained much momentum in recent years. Drawing from the theory of social norms, researchers demonstrated that providing feedback to residents on how their energy consumption compares to the average energy consumption of others leads to measurable reductions in energy consumption. This approach is called normative feedback and, after reading a study on this topic, a company

called OPOWER formed in 2008 and expanded this approach to hundreds of thousands of households across the United States. They incorporated the most salient research in the field and independent analyses have identified a resulting average energy savings of 2.0% (Alcott, 2011). The proposed research examines this extensive use of normative feedback and tests different variations of its implementation, with the overarching goals of defining its boundary conditions and improving it.

### 1.2 Research Questions

Given that normative feedback can change residential energy consumption behaviors, it becomes important to know a few more details of OPOWER's implementation of normative feedback. OPOWER works for various utility companies and thus the targeted residents also receive regular utility bills, holding them financially accountable for their energy consumption. The OPOWER program comes alongside this existing billing structure to provide residents with home energy reports, usually monthly, that inform them of their energy consumption as it compares to approximately 100 of their neighbors with similarly sized homes. These home energy reports, on average, have resulted in an overall energy savings of around 2%, with specific applications ranging from 1.4% to 3.1% (Alcott, 2011).

One potential boundary condition of this approach is that residents are held financially accountable for their energy consumption. But this is not always the case. For instance, in many apartment complexes and dorm rooms, residents do not receive utility bills. And for decades, residents of military family housing have not had to pay for their utility usage. While this is beginning to change, still more than two thirds of military family

housing residents do not pay utility bills (Jowers, 2012). Does normative feedback for energy consumption still yield energy savings when residents are not held financially accountable for their energy consumption?

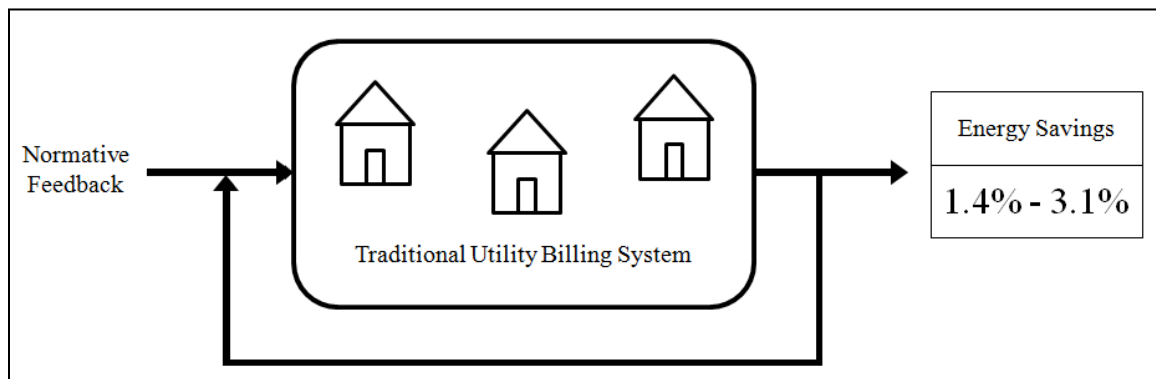
Also, the OPOWER home energy reports compare residents to approximately 100 of their neighbors. But who are these neighbors? A resident cannot be completely clear on this, because the comparison involves other homes of similar size that use the same fuel sources. While this would usually include many nearby homes, it could easily extend out well beyond the neighborhood. In applications other than energy efficiency, social norms research has shown that normative feedback is more powerful when describing the behavior of others who share the same “immediate situational circumstances” (Goldstein, Cialdini, & Griskevicius, 2008). Perhaps there is some ground to gain here. What if residents received comparisons to others only in their same neighborhood? Or on their same street? Or even to next door neighbors? Does normative feedback for energy consumption produce increasing savings as the proximity of comparisons increases?

Finally, what about more extreme applications of normative feedback? What about a normative-based utility billing system? Such a system would compare the utility consumption of each household to the average utility consumption of similar homes, and use this comparison as the basis for a monthly billing statement. If the household’s consumption is above average, they are billed for that over-consumption. If the household’s consumption is below average, they receive a credit for that under-consumption. And if the household’s consumption is within a certain buffer zone of the average, no payment or credit is due. How much energy savings would such a billing

system generate when implemented into a community previously not billed for utility usage?

### 1.3 Research Objectives

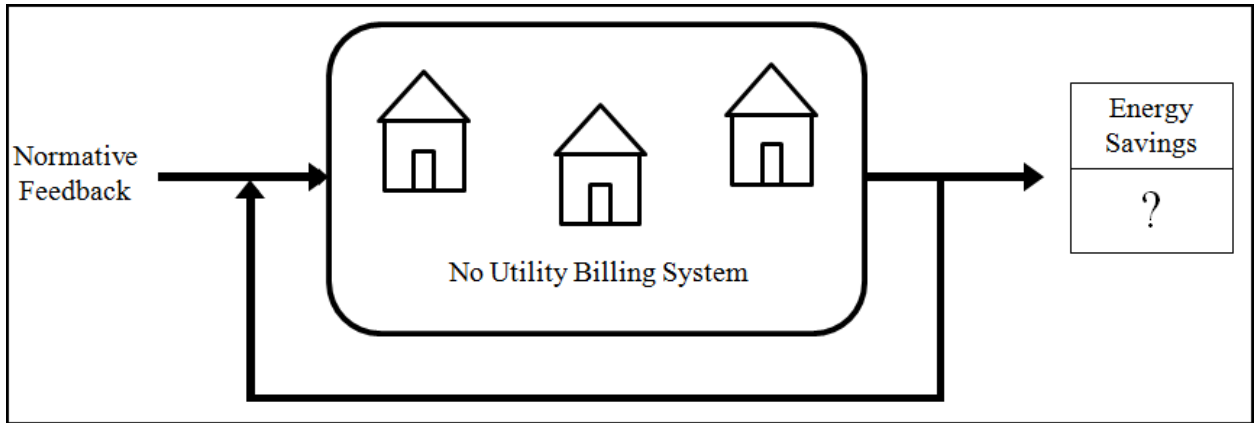
The objectives of the proposed research aim to answer the stated research questions. To begin framing the objectives, it is useful to envision the state of the art in normative feedback as a simple model. This basic model can then be varied in different ways to help answer the different research questions. Figure 1.1 provides a visual description of the basic model and its results.



**Figure 2.1** The Basic Normative Feedback Model

The first variation of the basic normative feedback model is shown in Figure 1.2, and it illustrates the application of the model in an environment with no financial accountability for residential energy consumption.

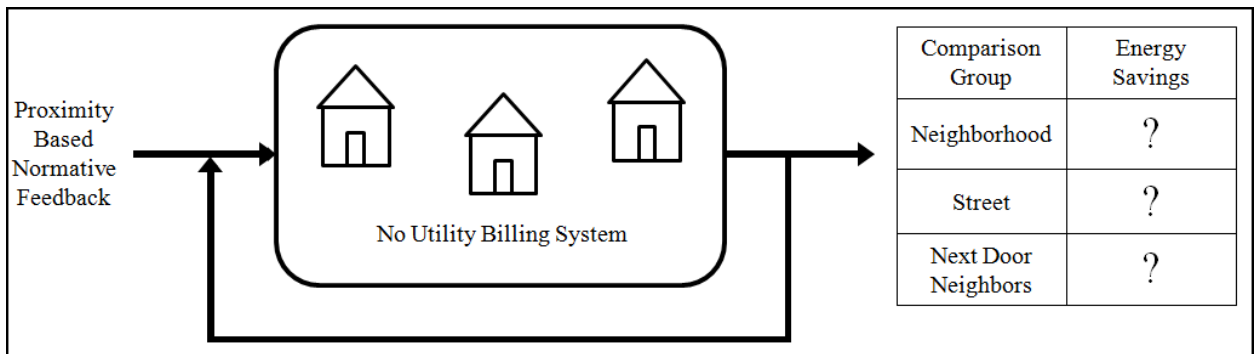
Research Objective 1: Determine whether normative feedback generates significant energy savings when applied to households that are not held financially accountable for their energy consumption.



**Figure 1.2** The Normative Feedback Model in Absence of Financial Accountability

The second variation of the basic normative feedback model is shown in Figure 1.3, and it illustrates changes in comparison groups according to proximity. This variation, when implemented, allows for assessment of the role of comparison group proximity on the energy savings produced by normative feedback.

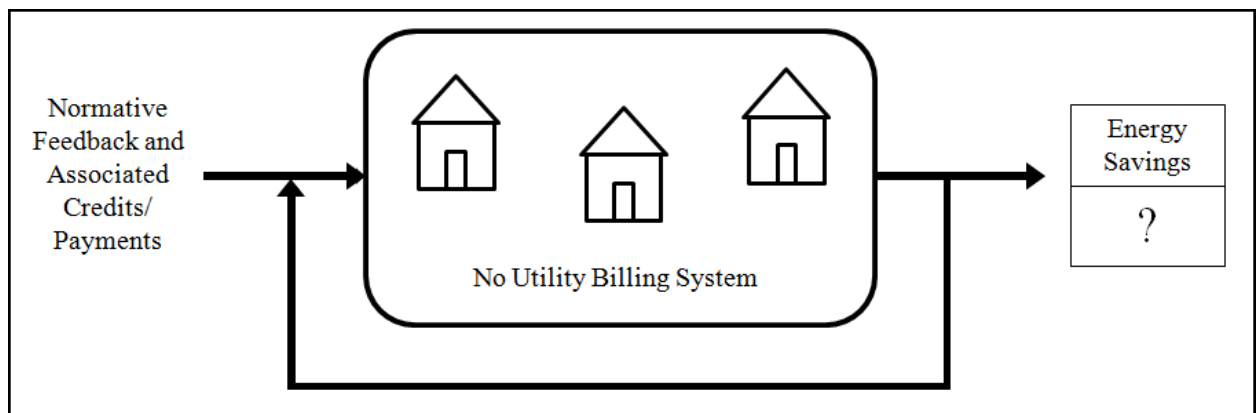
Research Objective 2: Determine whether significant differences exist in the household energy savings produced by normative feedback when comparison groups are altered according to proximity.



**Figure 1.3** The Normative Feedback Model with Proximity-Based Comparison Groups

The third variation of the basic normative feedback model is shown in Figure 1.4, and it illustrates the incorporation of a normative-based utility billing system. Such a system gives financial credits for below average energy consumption and extracts financial penalties for above average energy consumption.

Research Objective 3: Determine overall energy savings associated with the implementation of a normative-based utility billing system into a community previously not held financially accountable for household energy consumption.



**Figure 1.4** Normative Feedback as Basis for Utility Billing System

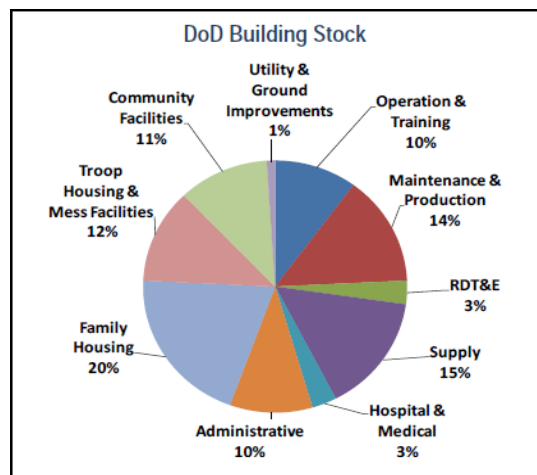
By testing these three variations of the basic normative feedback model in appropriate settings, the three research objectives can be met.

1.4 Research Context: Military Family Housing

In a speech at Buckley Air Force Base in Colorado in January of 2012, President Obama singled out the Department of Defense as “the world’s largest consumer of energy.” In fact, the Department of Defense consumed 80% of the total energy consumed by all agencies of the United States government in 2010 (Energy Information Administration,



2011). The president went on to praise the effort underway by all branches of the armed services to reduce energy consumption and help develop alternative energy sources. Indeed, energy has become a high priority in the military, both for financial reasons and to reduce dependence on foreign oil (Obama, 2012). While a majority of the energy spending is on jet fuel, the military still spends over four billion dollars a year on energy for facilities. Figure 1.5 shows the breakdown of those facilities by square footage, highlighting that the largest segment is military family housing, representing 20% of the facilities in the Department of Defense (Robyn, Department of Defense Facilities Energy, 2010). Thus, reducing the energy consumed in military family housing by even small percentages can lead to significant savings.



**Figure 1.5** Breakdown of Department of Defense Facilities (Robyn, 2010)

This makes military family housing an ideal place to focus energy efficiency efforts, because of the potential for highly scalable energy savings. If a program can be shown to yield significant savings at a low cost, it can be readily extended to other military bases throughout the Department of Defense. Also, since most of the research on influencing

human energy consumption behaviors has taken place in residential settings, that research should readily extend to military family housing. It can then be tested and improved upon.

## Chapter 2: Literature Review

### 2.1 The Role of Human Behavior in Residential Energy Consumption

A discussion of energy efficiency most usually ends up focusing on new technologies, economic incentives, and the thermodynamics of a building. What is often overlooked is the significant role that human behavior plays in energy consumption. The latest energy efficient gadget only saves energy when it replaces a less efficient model. A new programmable thermostat only saves energy when actually programmed correctly. And just because new attic insulation will reduce energy consumption and pay for itself in energy savings over several years, this does not automatically translate to large numbers of homeowners making the investment. From the temperature setting of hot water heaters to powering down printers, people make choices each day about their energy consumption behaviors. These choices have a significant impact on the quantity of energy consumed.

#### 2.1.1 The Potential of Behavior Change to Close the Energy Efficiency Gap

Traditional approaches to energy efficiency have focused primarily on the development and implementation of new technology. This has undoubtedly led to an increase in household energy efficiency. In fact, the amount of annual household energy consumed per capita has decreased from 48 million Btu in 1978 to 38 million Btu in 2007 (Ehrhardt-Martinez, Laitner, & Reed, 2009). And, there is more ground to gain in this area, with one study indicating that readily available technologies could be implemented for savings of more than 25 percent (Stern, 2008). But, it is also true that many

technology employments have not reached their full potential in terms of energy efficiency. Sometimes this is because individuals choose not to make an up-front investment, even if that investment will pay for itself within a short period of time. And sometimes, even if an individual purchases the technology, they may not use it in the intended way. For instance, a programmable thermostat only saves energy when it is actually programmed, for instance, to adjust the temperature when no one is home. If it is left to simply “hold” a steady temperature all the time, it will obviously not reduce energy consumption (Frader-Thompson, 2011).

This discrepancy between realized energy savings and potential energy savings, as it relates to the purchasing and implementation of cost-effective technology, is referred to as the energy efficiency gap (Jaffe & Stavins, 1994). In her testimony before a House of Representatives Subcommittee, Ehrhardt-Martinez (2009) describes an additional gap, called the attitude-behavior gap. This describes the discrepancy between people’s attitudes towards energy conservation and their actual behavior. A recent Gallup poll indicated that 77% of Americans are worried about the affordability and availability of energy and 85% even reported that they “should be spending thousands of dollars to increase the energy efficiency of their home.” However, less than two percent of the population is actually incorporating these attitudes into their actions in a significant way (Ehrhardt-Martinez, 2009).

This has all led to an increased interest in the role of human behavior in energy consumption, as evidenced by the increasing amounts of literature on the subject and by the more than 700 professionals attending the 2011 Behavior, Energy, and Climate

Change conference in only the fifth year of the conference's existence (Foster & Mazur-Stommen, 2012). Researchers from the social sciences and engineering fields are coming together to explore how a deeper understanding of people's energy consumption choices and activities can play a part in helping to close the two gaps described above. The resulting research over the last several years has produced much evidence that understanding and shaping human energy consumption behaviors can indeed significantly boost energy efficiencies (Gardner & Stern, 2008) (Ehrhardt-Martinez, 2008).

Two such studies have focused on the residential energy sector and have estimated that savings from household behavioral changes could be in the range of 20%. The first study identified a domain of actions that a household could take to reduce their energy consumption, such as getting rid of a second refrigerator. It then used a Monte Carlo method to account for the uncertainties both in the quantity of associated savings and in the adoption rates of the various actions. This study estimated savings of 8.6 quads ( $\pm 1.5$ ), which would be a 22% reduction in household energy consumption. This amount of savings is roughly equivalent to the total annual energy consumption of Brazil or South Korea and is slightly less than the total annual energy consumption of England (~10 quads) and France (~11 quads) (Laitner, 2010).

The second study used more of an economist's approach, incorporating estimates of "behavioral plasticity" to account for the uncertainty in the adoption rates of various energy saving behaviors. This study estimated savings of 20% in household energy consumption (Dietz, Gardner, Gilligan, Stern, & Vandenberg, 2009). It should be noted

that in both this study and the one previously described, household energy consumption is defined to include the operation of household vehicles as well.

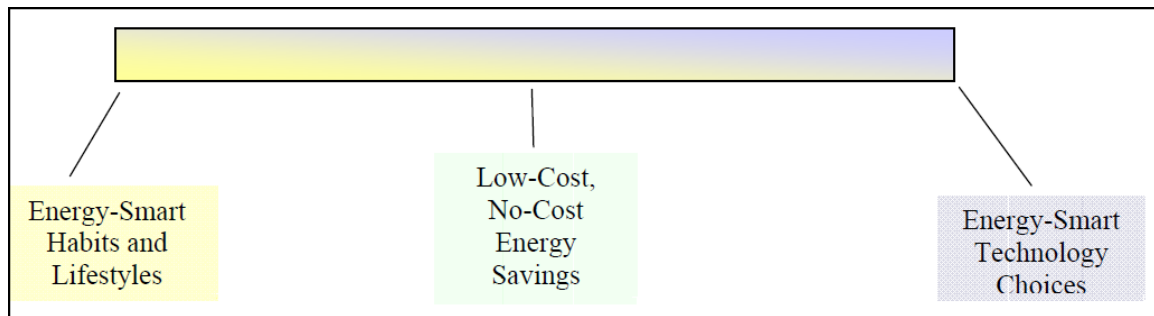
In calculating the estimated savings described above, both studies categorized potential energy saving actions. In the second study, the researchers specifically identified 17 behavior changes and grouped them into five different categories on the basis of behaviorally relevant attributes. These categories, shown in Table 2.1, reflect both the cost and frequency required for the behavior changes.

<b>Category of Behavior Change</b>	<b>Examples</b>
W actions: home <i>weatherization</i> upgrades of heating and cooling equipment	attic insulation, high-efficiency windows, replacing old HVAC units
E actions: more efficient non-heating and cooling <i>equipment</i>	adopting more energy-efficient appliances and equipment
M actions: equipment <i>maintenance</i>	changing air filters in HVAC systems
A actions: equipment <i>adjustments</i>	reducing laundry temperatures, resetting temperatures on water heaters
D actions: <i>daily</i> use behaviors	eliminating standby electricity, thermostat setbacks, line drying

**Table 2.1** Categories for Energy Conservation Behavior Changes (Dietz, et al., 2009)

Another approach to categorize potential energy-related behavior changes defines a Behavior Energy Response Continuum (Laitner, Ehrhardt-Martinez, & McKinney, 2009). This is shown in Figure 1.6. This puts all such changes on a continuum, with the left side

representing habits and lifestyles and the right side representing technology choices. In the middle are infrequent, low-cost or no-cost energy saving actions.



**Figure 2.1** The Behavior Energy Response Continuum (Laitner et al. 2009)

Regardless of the method of categorizing energy conservation behaviors, it is important to note the different characteristics of potential actions. In designing a program to reduce energy consumption, different target populations will have different inclinations towards the potential energy conserving actions. For instance, a population of renters, such as in military family housing, will not be inclined (in fact, usually not allowed) to install new windows or insulation. Only a homeowner would typically be willing to make such an investment. So a program designed for military family housing should not try to encourage the higher-cost technology investments represented by the right side of the continuum and by the Category W actions described previously (McMakin, Malone, & Lundgren, 2002).

To further underscore the importance of behavior in accomplishing significant energy savings, the city of Juneau, Alaska deserves mentioning. When an avalanche destroyed power transmission lines in April of 2008, the city had to rely on a bank of diesel-powered generators for their electricity production. The price of electricity increased

500% (Leighty & Meier, 2011). Within two weeks, Juneau had cut their electricity consumption by 20% and by May, their electricity use was down by 40% (Berkeley Lab News Center, 2008). This demonstrates that when people get serious about saving energy, they can quickly and significantly reduce their consumption. This accomplishment involved a large and coordinated effort. It involved quick energy audits of local businesses and a public campaign to engage people in the cause, encouraging them to unplug anything needlessly drawing power and replace incandescent bulbs with compact fluorescents. Also, the local utility provided feedback to the public, charting the progress made towards energy conservation. All of this facilitated the people of the city getting the message that in order to be good citizens they needed to take immediate steps to reduce their energy consumption (Berkeley Lab News Center, 2008). And it is also interesting to note that 8% of the energy savings persisted even after the crisis was over (Leighty & Meier, 2011).

### 2.1.2 Behavior-Based Energy Efficiency Interventions

While the story of Juneau provides a drastic example of what is possible when people get serious about the task at hand, the increasing amount of research in this subject area has produced numerous examples of intentional programs that have also effectively motivated people to alter their energy consumption behaviors. These conservation programs can be broken down into two categories: antecedent interventions and consequence interventions (Abrahamse, Steg, Vlek, & Rothengatter, 2005).

Antecedent interventions aim to influence behavioral determinants, such as knowledge, before the behavior occurs. This would include interventions such as commitments, goal



setting, information, and role modeling. A commitments intervention invokes an oral or written pledge or promise from the residents to change their energy consuming behavior. This commitment can be made to one's self, but it is more effective when made publicly. Goal setting is similar to the commitments approach, but attaches a specific goal, such as energy savings of five percent. The information intervention equips residents with knowledge on how to save energy and provides specific tips to that effect. And finally, the role modeling intervention directs attention to those who are already excelling in their energy conservation. These residents are highlighted in newsletters, mailings, or at public events, and their energy conservation behaviors are put forward as encouragement to their neighbors. A review of these antecedent interventions concluded that specificity and personalization usually lead to increased energy savings and that these interventions are most effective in combination (Abrahamse, Steg, Vlek, & Rothengatter, 2005).

Consequence interventions provide positive or negative consequences for energy consumption behaviors. Behaviors that decrease consumption receive positive consequences, while behaviors that increase energy consumption receive negative consequences. These types of interventions include rewards and feedback. A rewards program simply provides a reward as a positive consequence to energy conservation behavior. The reward is most usually a monetary incentive. Feedback programs provide residents with feedback on the amount of their energy consumption. The feedback can be monthly, weekly, daily, or continuous, and can sometime involve comparisons to other households. In this way, the feedback acts as a consequence to the household's energy

consumption and provides a reference point and motivation for behavior change (Abrahamse, Steg, Vlek, & Rothengatter, 2005).

While all of these different types of interventions have been shown to be effective at times and ineffective at times, it is generally agreed that particular combinations increase effectiveness. For instance, a household might make a public commitment to reach a certain goal and then receive feedback each month on their progress towards that goal. Such an example would combine commitment, goal setting, and feedback, thus strengthening the potential impact of the intervention.

One important issue in evaluating different behavior-based energy efficiency interventions is the issue of scale. If a particular intervention demonstrates an ability to generate high levels of energy savings, but it requires extensive resources and tailoring for each individual household, it may not be realistic to apply that intervention across a wide region of homes. For instance, a particular program at Travis Air Force Base used personalized coaching, rewards, and electronic information displays in the home to generate 18% savings (Balfour Beatty, 2010). But this study involved only 21 households and would require a large investment of time and money to implement at a large scale. This sort of an intervention can also be referred to as an opt-in strategy, in that residents have to be willing to participate. In contrast, an opt-out strategy automatically includes residents in the program unless they take action to declare their unwillingness to participate. This allows for opt-out interventions to obtain significantly higher participate rates (Ehrhardt-Martinez, Donnelly, & Laitner, 2010).

One particular application of an opt-out feedback intervention has demonstrated an ability to generate energy savings at an extremely large scale. A company named OPOWER has incorporated academic research on social norms to provide customized feedback to hundreds of thousands of households across the United States. This approach relies on comparing a household's energy consumption to that of other households in the area. It is a simple approach that extends easily across large regions. The roots of this idea grew in the social sciences over the last several decades.

## 2.2 Social Norms Theory Applied to Energy Efficient Behaviors

Social norms theory essentially states that people often pattern their behaviors after what they perceive to be normal social behaviors. As will be explained more fully below, this theory has led to many applications in the area of alcohol consumption of college students. In such an application, the focus is on correcting the difference between what a student perceives as socially normal behavior and what the actual socially normal behavior is. But social norms also have application strictly as a type of feedback. By providing people with information on socially normal behavior, they may then be inclined to alter their own behavior towards the behavior most often chosen by others. This can be a helpful tool in modifying the behavior of communities. In the context of household energy efficiency, the provision of feedback on the energy consumption of other households can prompt a change in energy consumption behavior.

### 2.2.1 Foundational Applications of Social Norms Theory

As far back as 1936, the term "social norms" has been used in the fields of sociology and social psychology (Sherif, 1936). A formal definition of social norms theory states that

“people tend to adopt group attitudes and act in accordance with group expectations and behaviors based on affiliation needs and social comparison processes, social pressures toward group conformity, and the formation and acquisition of reference group norms.” This definition points out that people tend to alter both their attitudes and behaviors towards what they perceive as normal attitudes and behaviors. The establishment of this theory resulted from a large amount of literature throughout the twentieth century that demonstrated group norms as an independent variable with high explanatory power in predicting individual attitudes and behavior (Perkins W. H., 2002).

One of the more well-known studies on social norms used littering in public places as its context. In this study, subjects returned to their cars in a university hospital parking garage. On their way to their cars, they witnessed a student dropping a handbill onto the ground. Two experimental conditions existed while observing the student litter. In one condition, the surface of the parking garage was covered in similar litter. In the other condition, the surface was still littered, but all the litter had been swept into three neat piles. When the subjects reached their car, they found an identical handbill on their windshield, and the study monitored the percentage of individuals in each condition who chose to drop the handbill to the ground before driving away. In the scattered litter condition, 45% of the subjects littered, while in the swept piles condition, only 18% of the subjects littered. Previous research had already established that subjects are more likely to litter into an environment that is already littered. The value of this study lies in the fact that while both conditions contained littered environments, subjects behaved differently when the litter was swept into piles. That is, they encountered a *descriptive*

*norm* demonstrating that many others were littering, but they also encountered an *injunctive norm* demonstrating that such littering is not okay and needs to be cleaned up (Cialdini, Reno, & Kallgren, 1990). This distinction between descriptive and injunctive norms is important and will be referenced further on in this literature review.

Over the last twenty five years, researchers have begun to find more practical applications for social norms. Beyond just the ability of social norms to *explain* aspects of human behavior, some social psychologists began using their knowledge about social norms to *influence* human behavior. Specifically, as stated before, they focused on the issue of excessive drinking of alcohol among college students. Two researchers, H. Wesley Perkins and Alan Berkowitz, found a pattern of misperceptions among students with regard to levels of drinking among their peers. They found that students typically overestimated how often and how much their peers were drinking, and typically regarded their peers as more permissive in their attitudes toward drinking than they actually were. Based on social norms theory, if students perceived norms for drinking that were different than the actual norms, they would likely be targeting the “wrong” norms in their social drinking behavior. Thus, these researchers suggested that correcting these misperceptions could reduce dangerous overconsumption of alcohol among college students (Perkins & Berkowitz, 1986).

A number of subsequent studies at various institutions followed this suggestion. They designed and implemented programs to measure actual high-risk drinking rates and then inform students of those actual rates. They consistently found that correcting student misperceptions about typical drinking behavior on their campus led to significant

reductions in high-risk drinking rates by as much as 20%. This strategy of communicating actual social norms to dispel misperceived social norms is often referred to as the *social norms approach*. (Perkins W. H., 2002)

According to the National Social Norms Institute at the University of Virginia, most research in the field of social norms breaks down into two general categories. The first category involves the social norms approach that has already been described. The second category does not involve a correction of misperceived norms or even an attempt to measure perceptions, but simply provides feedback on actual norms and measures any resulting changes or differences in behaviors or attitudes. This approach is referred to as *normative feedback* (National Social Norms Institute, 2012).

A recent study demonstrated the power of normative feedback in motivating environmental conservation. This study examined the effectiveness of signs in hotel rooms requesting guests to reuse their towels. The control group had standard signs hung in the bathrooms that made an environmental appeal for guests to reuse their towels so that resources could be conserved. The test group signs, in addition to the environmental appeal, contained a descriptive norm that essentially stated, “The majority of our guests reuse their towels.” This normative messaging proved superior to the environmental-only appeal, increasing the towel reuse rate from 35% to 44%. Of additional interest is that, on a second round of this experiment, normative messaging was modified to state, “The majority of our guests in this room reuse their towels.” The authors refer to this as a *provincial norm*, when a proximity identifier is added to the descriptive norm. They

found that towel reuse increased to 49% in rooms receiving the provincial norm messaging (Goldstein, Cialdini, & Griskevicius, 2008).

### 2.2.2 Normative Feedback for Energy Efficient Behavior

As more normative feedback studies reported results, many described positive results. That is, the normative feedback produced the intended effect. However, some studies found no substantial effects and some studies found undesirable effects (Fischer, 2008). Much of the problem, it seemed, stemmed from what is known as the *boomerang effect* (Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007). Since the theory of social norms indicates behavior change towards perceived normality, the resulting behavior change from a correction in perceived norms might be a positive change or it could be a negative change. For instance, with regard to providing normative feedback on home energy consumption, it is expected that an over-consuming household would adjust their behaviors to reduce their overall energy consumption in order to be more in line with the norm. This would be viewed as a positive change. But a household that is already demonstrating the desired behavior by under-consuming energy may respond to the normative feedback by relaxing their energy efficient behaviors, and in so doing become more normal. That is, they may actually increase their consumption as a result of receiving normative feedback on their energy consumption. This phenomenon is known as the boomerang effect.

A field study on aspects of this boomerang effect that began applying the theory of social norms to energy consumption behaviors. The research team designed an experiment to see if the use of injunctive norms could eliminate the undesired boomerang effect. As

alluded to before, descriptive norms simply describe normal behavior, while injunctive norms attach an element of social approval or disapproval to a given behavior. The research involved placing doorhangers throughout a neighborhood, with each doorhanger containing normative feedback regarding that household's electricity consumption. Half of the subject households received only descriptive normative messages, detailing the average neighborhood electricity consumption. These messages produced electricity savings amongst high electricity consumers, but increased electricity consumption amongst low electricity consumers. This demonstrated the presence of the boomerang effect. The other half of the subject households received doorhangers that contained similar descriptive normative information but with an injunctive message also included. The injunctive message was a smiley face emoticon (☺) if the household had consumed less electricity than the average, and a sad face emoticon (☹) if the household had consumed more electricity than the average. The effect of this injunctive message was to significantly reduce the undesired boomerang effect. On average, the households that were consuming electricity at below average rates continued to consume at the same below average rates, instead of increasing their consumption as did the low-consuming households which did not receive the injunctive messaging (Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007). This study provides strong evidence that injunctive norms can counter the boomerang effect.

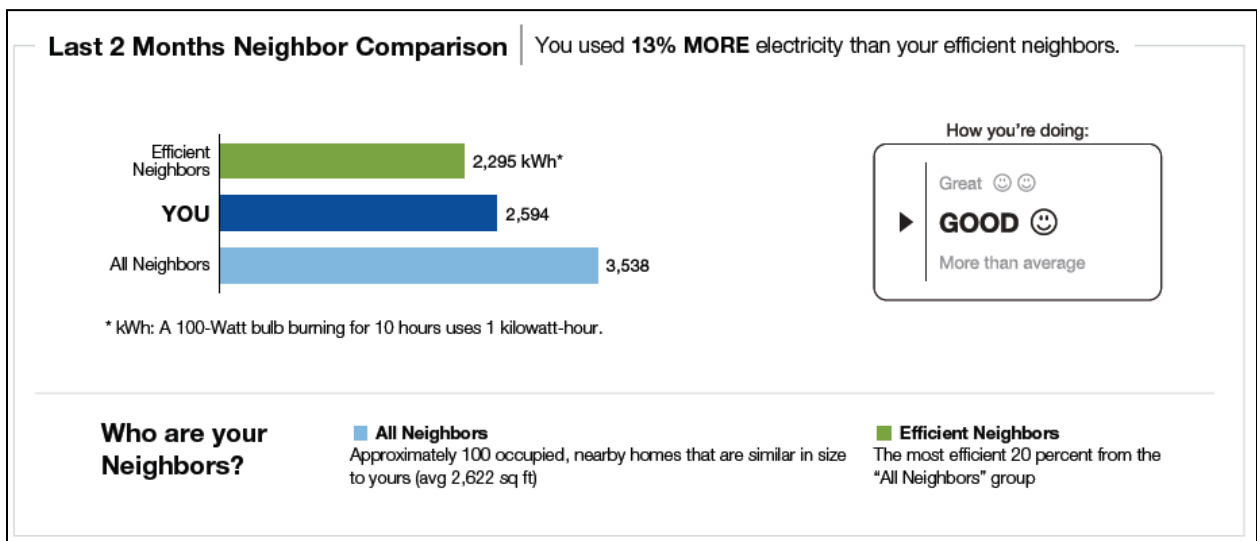
### 2.2.3 OPOWER's Large-Scale Application of Normative Feedback

It was the study just described that got the attention of the founders of OPOWER (Alcott, 2011). If the boomerang effect could be avoided, allowing the highly-reproducible



normative feedback to generate significant energy savings, they realized the potential to apply the intervention on a very large scale. OPOWER uses home energy reports as the mode of providing normative feedback to residents. These home energy reports are mailed to residents on either a monthly, bimonthly, or quarterly basis, depending on the billing cycle of the respective utility company. The reports contain a comparison between the household's energy consumption data and the average consumption of approximately 100 neighbors with similarly sized homes that are fueled by the same energy sources (i.e. electricity only or electricity and natural gas). This information represents the descriptive norms discussed previously. The reports also contain injunctive norms to counter the boomerang effect. This is accomplished through the use of emoticons (☺) to indicate social approval for low energy consuming behavior.

Figure 2.2 contains a sample comparison from one of OPOWER's home energy reports.



**Figure 2.2** Sample of Normative Feedback in OPOWER's Home Energy Reports

As is evident on the sample, OPOWER includes an additional layer of comparison. They compare the household to “Efficient Neighbors,” the most efficient 20 percent of neighbors, that is the lowest 20 percent of consumers. This provides additional motivation for households consuming at below average levels but still with room for improvement, helping to further counter the boomerang effect. The reports also contain tips for residents on how to actually go about lowering their energy consumption. And it should also be noted that while the sample in Figure 2.2 compares strictly electricity consumption, OPOWER also sends reports to dual fuel households. In such cases, energy consumption can be compared by converting electricity usage from kWh to kBtu and converting natural gas usage from ccf to kBtu and then simply adding to obtain a total value for household energy consumption in kBtu.

OPOWER began their work in 2008 by mailing home energy reports to 35,000 households within the footprint of Sacramento Municipal Utility District. An analysis completed after one year of mailings demonstrated a significant difference in energy consumption between treatment and control groups, representing an energy savings of 2.1% (Ayres, Raseman, & Shih, 2009). Since then, OPOWER has continued to expand its reach, partnering with over 50 utility companies in 22 states across the United States (Crawford & Fischer, 2011). Multiple independent analyses have demonstrated associated energy savings between 1.5% – 3.5% (Ayres, Raseman, & Shih, 2009) (Agnew, Niu, Tanimoto, Goldberg, & Wilhelm, 2010). The most comprehensive analysis observed 22 million utility bills from nearly 600,000 households, encompassed twelve different utility companies, and determined that the implementation of

OPOWER's home energy reports program yields an average energy savings of 2.0% (Alcott, 2011). They seem poised to continue their growth, with California Public Utilities Commission now allowing investor-owned utilities to claim energy savings that result from behavior-based efficiency programs (Smith & Sullivan, 2011).

### 2.3 Identification of Knowledge Gaps

With the use of normative feedback so quickly emerging as a highly cost-effective means of changing resident behavior, research in the field has accelerated. But there remain some significant gaps in the body of knowledge. Opportunities exist to evaluate the application of normative feedback to households that do not have financial incentive to conserve energy, and the consideration of proximity in defining comparison groups for normative feedback.

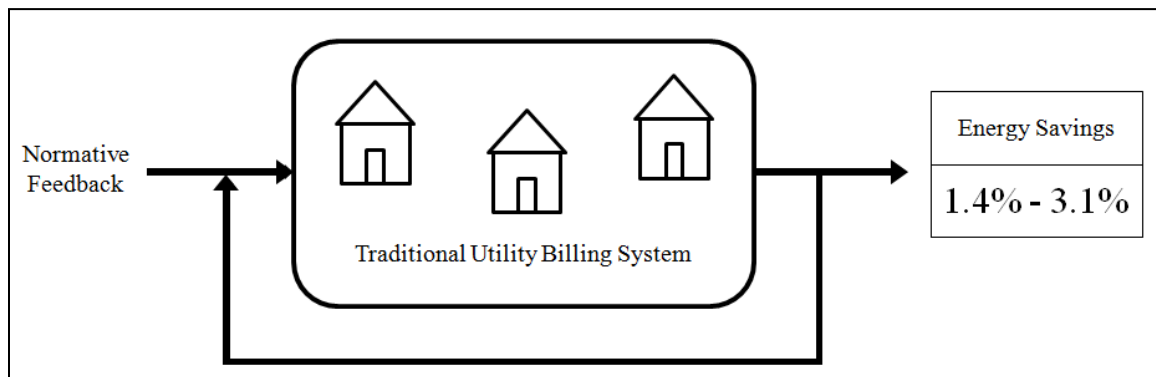
The application of normative feedback to energy consumption necessarily occurs within the confines of certain boundary conditions. For instance, the target behavior, namely energy conservation, has widespread social approval, is private, is reoccurring, and perhaps most significantly, has a direct personal benefit in terms of money saved from reduced utility bills. It is not known whether normative feedback can produce energy savings in the absence of financial incentives. And, just as the application of normative feedback to energy consumption grew out of the field of social norms, so the results can feed back in to that same field for other applications. It is not known, for instance, if injunctive norms can counter the boomerang effect when individuals are not financially motivated to demonstrate a particular behavior (Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007). Such knowledge would inform the application of normative

feedback to other areas such as alcohol consumption, littering, and illegal downloading of music.

Heretofore the application of normative feedback to energy consumption has almost exclusively based comparisons on either a neighborhood average or the average of approximately 100 nearby homes. One study did investigate the differential effects of comparing household consumption to country, regional, or neighborhood averages. That study found that low energy consumers increased their consumption when compared to national averages, but reduced their consumption when compared to neighbors (Loock, 2011). It is not clear how much consumption increased or decreased or whether or not injunctive norms were included with the feedback. What remains to be discovered is the effect of increasing the proximity of comparison within the neighborhood level. A study on normative feedback for college alcohol consumption found that increasing norm proximity, in this case how well the subject knew those in the comparison group, increased the impact of the feedback (Cho, 2006). This concept of increasing the relevancy, and resulting impact, of normative feedback by increasing the proximity of the comparison group has not been tested on energy conservation behaviors.

## Chapter 3: Home Energy Report Experiment

In response to the knowledge gaps identified in the literature review and further research needs described in this chapter, an experiment was conducted to test variations of the basic normative feedback model in order to contribute to the rapidly expanding field of human factors in energy efficiency. Because of the large scale and prominence of OPOWER's work, the basic normative feedback model is framed upon their processes and results. This simple model and its variations facilitate the discussion of the purposes and hypotheses of the home energy report experiment. Figure 3.1 below depicts again the basic normative feedback model.



**Figure 3.1** The Basic Normative Feedback Model

### 3.1 Experiment Purposes and Hypotheses

The home energy report experiment assesses two variations of the basic normative feedback model. As will be evident in the proceeding sections, the second variation, in its implementation, is really more of a sub-variation of the first. They are framed as separate variations in this research because they answer distinctly separate research questions. One feature of this research framework is that it allows an experiment aimed

at testing the second variation to inherently provide testing of the first variation as well. Thus, the home energy report, as described in this chapter, will be used to test two variations of the basic normative feedback model.

### 3.1.1 Variation 1: Normative Feedback in Absence of Billing System

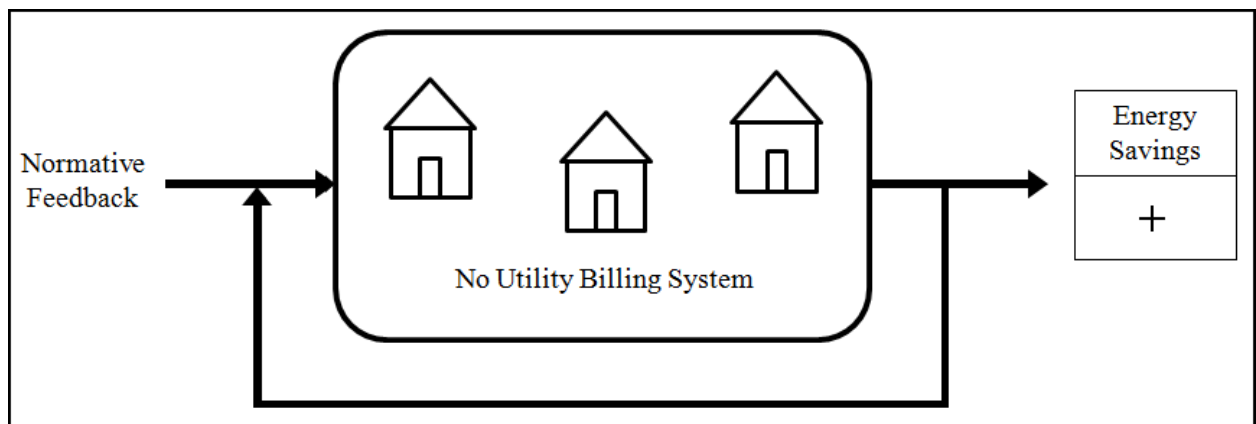
The first variation of the basic normative feedback model alters the environment into which the normative feedback is applied. It changes the boundary condition of financial incentives. Previous applications of normative feedback have focused on households that exist within a traditional utility billing system, such that residents are financially motivated to conserve energy. The less energy they consume, the lower their utility bills will be. And conversely, the more energy they consume, the higher their utility bills will be. The first variation of the basic model allows for testing on whether normative feedback can produce energy savings when no utility billing system is in place.

This carries importance beyond contributing to the field of social norms. If normative feedback can be shown to produce energy savings even when no billing system is in place, it could be extensively applied to such settings. Many university dormitories and apartment complexes do not currently bill residents for their utility usage. And although the military is slowly incorporating utility billing programs into military family housing, the full transition will take at least six more years. Currently, two-thirds of households on military bases are not held financially accountable for their utility usage (Jowers, 2012). Even incorporating normative feedback while details of different billing programs are worked out could lead to significant energy savings.

The foundational research on normative feedback was never constrained by the boundary condition of financial incentives for behavioral choices. In applications such as littering and alcohol consumption, subjects were not motivated to behave one way or another due to any financial incentives. Yet, normative feedback still influenced their behaviors.

Therefore, the proposed research makes the following hypothesis:

Hypothesis 1: Normative feedback on residential energy consumption will still produce positive energy savings even when residents have no financial incentive to conserve. This hypothesis is represented in Figure 3.2.



**Figure 3.2** Hypothesis 1: Positive Energy Savings in Absence of Billing System

### 3.1.2 Variation 2: Proximity Based Normative Feedback

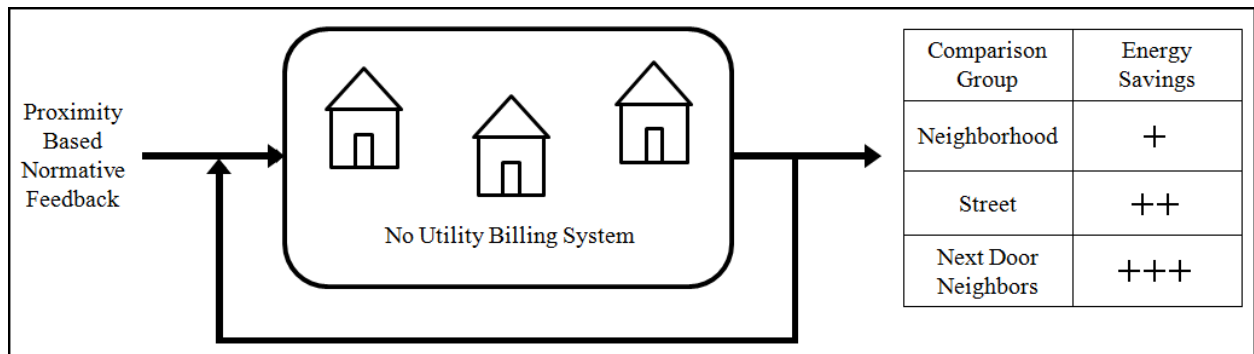
The second variation of the normative feedback model alters the comparison groups upon which the normative feedback is based, in order to test differences in energy savings as the proximity of the comparison group changes. While no study has tested this aspect of normative feedback for energy consumption, one study did develop some guidelines for comparison groups, though this was only based on resident surveys. The study noted that

shrinking the geographical scope of comparison groups improved the quality of comparison, and highlighted street name as a promising comparison group (Iyer, Kempton, & Payne, 2006). Thus, the proposed research intends to establish a “Street” comparison group, as well as one level of decreased proximity, “Neighborhood”, and one level of increased proximity, “Next-Door Neighbors.”

This variation of the basic model is motivated by research that has applied normative feedback in other areas. For instance, the hotel room towel study previously described found that hotel guests were more likely to reuse their towel when exposed to normative feedback on the reuse rates of other guests who had stayed *in the same room*, versus just being compared to other guests who had stayed anywhere throughout the hotel (Goldstein, Cialdini, & Griskevicius, 2008). This can be described as increasing the proximity of the comparison. Applying this understanding to residential energy consumption leads to the following hypothesis:

Hypothesis 2: Increasing the comparison group proximity in normative feedback for residential energy consumption will increase the amount of energy savings.

This hypothesis is represented in Figure 3.3.



**Figure 3.3** Hypothesis 2: Increased Energy Savings with Increasing Comparison Group Proximity



### 3.2 Experiment Design

These two variations of the normative feedback model have been tested through a controlled experiment that involved mailing home energy reports to households at Joint Base Andrews in Maryland. The home energy report experiment spanned four consecutive summer months, from June to September of 2012, with three mailings sent out during that span. The June energy consumption data produced the June home energy reports, and the impact of those reports was determined by analyzing July consumption data. This process was repeated three times, with the final iteration being the August home energy reports, of which the impact was determined by analyzing September consumption data. This process produced, therefore, three months of consumption data (July, August, September) that can be used to analyze and determine the impact of the home energy report mailings. The homes at Joint Base Andrews are individually metered and no billing program is in place, making this an appropriate setting for testing these two variations of the model. The homes are owned by Clark Realty Group and they granted permission for this experiment.

#### 3.2.1 Military Family Housing at Joint Base Andrews

Joint Base Andrews has been known as Andrews Air Force Base until the most recent round of Base Realignment and Closure (BRAC). Joint Base Andrews has privatized housing, which means that Clark Realty Group used its capital to build and renovate homes on the base and thereby became the owner of those homes. As the owner, they now receive rent payments each month from the government. The rent money comes

from the budgeted housing allowances the military members would have received if they lived in a home outside the base.

The housing office at Joint Base Andrews provided a master database of the homes on the base. According to that database, the housing stock contains 770 homes that exist within 12 different neighborhoods and on 30 different streets. 192 of these homes have been built since 2005, and 359 of the older homes have been renovated since 2005. Unit types include single family homes, duplexes, and townhouses. The homes are individually metered for utilities, to include water. They are fueled by both electricity and natural gas. While no utility billing program is currently in place, Clark Realty Group has recently hired a company to implement and manage such a program. The data available for the experiment were monthly electricity (kWh) and natural gas (ccf) usage data for each household, however the natural gas meter readings have not yet been deemed reliable by Clark Realty Group, so only electricity usage data was used in this experiment. This lack of reliable natural gas data is of little consequence, because the experiment took place during summer months when electricity-powered air conditioning units dominate the energy consumption of a typical home in the region, as opposed to winter months when gas-powered furnaces dominate the energy consumption.

### 3.2.2 Description of the Home Energy Reports

The home energy report experiment involved mailing normative feedback on household energy consumption to households in three different test groups, with the test groups varying from each other only in the comparison level of the normative feedback contained in the home energy reports they received. That is, they varied in whether their

energy consumption was compared to the average energy consumption of the entire neighborhood, their street only, or just their next-door neighbors. This normative feedback was modeled after OPOWER's home energy reports, as that is a format that has proven effective. The reports include descriptive norms, in that they compare the previous month's electricity consumption of the household to that of other households. These descriptive norms are presented in a horizontal bar chart format. There are three bars on the chart, one for the monthly electricity consumption of each of the following: 1) the subject household, 2) the average for the households in the applicable comparison group, and 3) the average for the most efficient 20% of the households in the applicable comparison group. The ordering of the three bars is in ascending order, such that the bar with the lowest value (representing the lowest consumption) is at the top. This represents a subtle injunctive norm because it implies a performance ranking of the three groups of households. The subject household can infer that they are doing better than or worse than other households simply based on whether they are listed above or below the other households.

The home energy reports also include some less-subtle injunctive norms, offering further indication of social approval or disapproval for energy efficient behavior in the form of labels and emoticons. If a household consumed less electricity than both the comparison group average and the most efficient households in the comparison group, they are labeled as "Great" and receive two smiley face emoticons. If a household consumed less electricity than the comparison group average, but more electricity than the most efficient households in the comparison group, they are labeled as "Good" and receive one smiley

face emoticon. If a household consumed more electricity than both the comparison group average and the most efficient households in the comparison group, they are labeled as “More than Average” and do not receive any smiley face emoticons. These labels and emoticons are contained in the home energy reports inside a box titled “HOW YOU’RE DOING” just to the right side of the bar chart. Figure 3.4 shows these three different forms of the normative feedback that vary depending on the subject household’s energy efficiency performance the previous month.



**Figure 3.4** Three Different Performance Categories: “Great,” “Good,” or “More than Average”

The data presented in the home energy reports are in watt-hours per square feet ( $\text{watt}\cdot\text{hr}/\text{ft}^2$ ). While the kilowatt-hour (kWh) unit is the commonly accepted unit for measuring electricity consumption for utility billing purposes, the comparisons in these home energy reports needed to account for the varying house sizes throughout the villages on Joint Base Andrews. In some villages, single family homes and townhomes are found within the same neighborhood, and to compare these homes without normalizing the data to account for the different sizes would greatly increase the chance of the comparison being dismissed by residents as unfair or not meaningful. To account for this, the raw monthly electricity usage for each household (in kWh) was divided by the size of the home (in  $\text{ft}^2$ ). This left the data with units of  $\text{kWh}/\text{ft}^2$ , but values in the range of 0.3 to 1.3. These low values would rely on numbers to the right of the decimal point to differentiate between households, which would be confusing and distracting to residents. So, the values were multiplied by 1,000, leaving the data with units of  $\text{watt}\cdot\text{hr}/\text{ft}^2$ , and values in the range of 300 to 1,300, which would be more digestible to residents.

The reports also included tips on how to reduce household energy consumption, and these tips were based on recommendations from the Department of Energy for homeowners interested in reducing their energy consumption (Department of Energy, 2012). These tips were tailored in two ways: 1) for military family housing, in that they do not include any recommended upgrades to the home itself, such as insulation or new windows, as the residents do not own the homes; and 2) for the summer season in which the experiment

took place, in that the tips included encouragement to raise the thermostat setting, as opposed to lowering it in the winter season.

Each home energy report was mailed in an envelope displaying the address of the housing office, “Liberty Park at Andrews”, as the return address and simply stated “Resident” as the name of the addressee. Along with a customized home energy report with the household address at the top, each mailing also included a brief cover letter explaining that this effort was part of a research project and that the energy report should not be considered a bill. This avoided confusion among residents and was a necessary condition for permission to conduct the experiment. The cover letters were essentially the same from month to month, and the cover letter for June is included as Appendix A. The home energy reports were generated in Microsoft Word with graphs imported from Microsoft Excel.

### 3.2.2 Categories of Comparison

As described in the previous section, the home energy reports categorize households based on their performance during the previous month. This categorization takes place within a larger categorization, that of the treatment categorization. Before energy consumptions could be compared and home energy reports generated, households had to first be categorized into the three different treatment categories. The treatment groups varied only by comparison level. That is, their monthly energy consumption was compared to the average energy consumption of either: 1) their entire neighborhood, 2) all the households on their street, or 3) their next-door neighbors.

In the “Neighborhood” treatment group, households received home energy reports that compared their monthly electricity usage to the average electricity usage of all the occupied households in their neighborhood. Table 3.1 provides a listing of the 12 different neighborhoods on Joint Base Andrews along with the number of households in each neighborhood.

<b>Neighborhood</b>	<b>Number of Households</b>
Adams Circle	35
Airey Court	6
Cleveland Square	61
Fairway Drive	13
Jefferson Village	95
Lincoln Place	81
Madison Cove	64
Monroe Gardens	119
Roosevelt Court	125
Truman Place	104
Washington Estates	13
Wilson Square	54
Total	770

**Table 3.1** Neighborhoods on Joint Base Andrews

In the “Street” treatment group, households received home energy reports that compared their monthly electricity usage to the average electricity usage of all occupied households on their street. Table 3.2 provides a listing of the 30 different streets on Joint Base Andrews along with the number of households on each street.

Street	Number of Households
Airey Court	6
Ashwood Circle	23
Atlanta Avenue	12
Bedford Drive (2000's)	48
Bedford Drive (2200's)	19
Beech Lane	18
Cedar Drive	2
Chicago Drive	61
Columbus Circle	35
Dawson Court	18
Dogwood Lane	12
Edgebrook Drive	52
Elm Lane	14
Fairway Drive	13
Lahm Court	23

Street	Number of Households
Laurel Drive	41
Madison Drive	26
Maple Lane	13
McCullin Court	24
Rosewood Drive	45
Spruce Court	54
Taylor Run	16
Tucson Avenue	38
Vandenburg Drive	13
Washington Drive	7
Waterview Court	19
West Perimeter Road	26
White Court	16
Wilmington Drive	43
Yuma Road	33
Total	770

**Table 3.2.** Streets on Joint Base Andrews

In the “Next-Door Neighbor” treatment group, households received home energy reports that compared their monthly electricity usage to the average electricity usage of four neighboring households, specifically the nearest two occupied households on each side of the treatment household. Maps provided by the housing office at Joint Base Andrews were used to determine the appropriate comparison houses for each treatment house. Figure 3.5 shows the bar charts from the home energy reports that made comparisons at these three different proximity levels.





**Figure 3.5** Three Different Comparison Categories: “Neighborhood,” “Street,” or “Next-Door Neighbor”

As noted before, within each of the three treatment categories, households were further categorized each month according to their energy performance. Within each treatment group, households were categorized as “Great,” “Good,” or “More Than Average.”

Thus, there were essentially nine different types of reports that a treatment household could possibly receive in any given month of the home energy report experiment. Table

3.3 provides a simple matrix portraying these nine different types of reports, and Appendix B provides a sample of each of these nine types of reports. It should be noted again here that within each report type, each household received a customized home energy report specific to their household each month.

		Performance Category		
		Great (GRT)	Good (GD)	More than Average (MTA)
Comparison Category	Neighborhood (N)	N, GRT	N, GD	N, MTA
	Street (S)	S, GRT	S, GD	S, MTA
	Next-Door Neighbor (NDN)	NDN, GRT	NDN, GD	NDN, MTA

**Table 3.3** Nine Different Category Combinations on Home Energy Reports

As can be seen in the home energy reports in Appendix X, each report also contains clarification on just who the household is being compared to. This is found in the section just below the horizontal bar chart. The question is spelled out: “WHO ARE YOUR NEIGHBORS?” In the space to the right of the question is found the answer that explains whether the household was compared at the Neighborhood, Street, or Next-Door Neighbor level. The answer also explains that only occupied homes were included in the comparison and that the “Most Efficient Neighbors” are the most energy efficient 20% of the households in the comparison.

### 3.3 Experiment Execution

The home energy reports were mailed to three treatment groups which were initially comprised of 75 households each. But before any mailings could be sent, the households on Joint Base Andrews had to be randomly placed into the three treatment groups. All households not in one of the three treatment groups were considered part of the control group. Aside from receiving the reports, households in the treatment group were not treated any differently than households in the control group. The households in each group were randomly selected from the neighborhoods across Joint Base Andrews. The households in each of the three treatment groups received the same personalized home energy reports, except that the category of comparison differed.

#### 3.3.1 Random Selection of Treatment Households

It was expected that the sample sizes would decrease substantially by the end of the experiment, due to the high turnover rates of military personnel, who usually move every two to four years and usually in the summer. As this experiment took place during the summer months, it was anticipated that approximately one third of the residents in the study would move during the course of the experiment. Consumption data from any household that experienced a move during the study was thrown out. This was accounted for in the selection of sample sizes. In each experimental group, 75 households would produce 225 observations over three months. Anticipating 33% getting thrown out, that would leave about 150 observations in each experimental group, which would allow enough statistical power to demonstrate differences between the treatment groups. This anticipated attrition in treatment households proved to be pretty close to what actually

happened, as will be discussed further along in this chapter. Table 3.4 provides a summary of the treatment groups and the initial number of households in each.

<b>Treatment Group</b>	<b>Comparison Level</b>	<b>Initial Number of Households</b>
1	Neighborhood	75
2	Street	75
3	Next Door Neighbors	75

**Table 3.4** Treatment Groups for Home Energy Report Experiment

The master database of houses, provided by the housing office at Andrews, included 770 houses. However, not all 770 houses could participate in the experiment. Some of the houses were unoccupied during certain months of the experiment. Some of the houses had no metered data or faulty meters. Some of the houses were designated for general officers and were not eligible for treatment, so as to not risk disruption to the experiment if a high-ranking officer took issue with their home energy report. There were only eight general officer residences, so this did not lead to a significant reduction in eligible homes for the experiment.

With regard to occupancy, only the data from houses that were fully occupied for the entire duration of the experiment were analyzed as treatment or control households. This ensures that homes only partially occupied during a given month will not be unfairly compared to homes occupied for the entire month. It also ensures that all the homes analyzed in the experiment had the same occupants during all four months of the experiment. In order to remove unoccupied or partially occupied homes from the analysis, the housing office at Joint Base Andrews provided the necessary occupancy

data. In fact, for the month of June, the occupancy data also included forecasted moves for the coming months. This allowed for the removal of probable movers before making selections of treatment and control households, thereby reducing the number of treatment and control homes that would have to be thrown out during the course of the experiment due to a move.

With regard to problematic meters, no additional data was required from the housing office. Some of the usage data simply contained blanks or “0” as the electricity consumption for certain homes. These homes were removed from the analysis. Also any home that was double listed with two differing meter reads or a reading of less than 50 kWh was considered unrealistic and removed from the analysis. This value was chosen after graphing the distribution of June electricity usage and noticing a reasonable breaking point around 50 kWh.

Removing homes from the dataset as described in the preceding paragraphs led to a dataset of homes that were eligible for the home energy report experiment, either as treatment or control homes. This dataset of eligible homes included 601 homes, which means that 169 homes were removed from the master dataset of 770 homes for the reasons described above. From this dataset of eligible homes, a random selection process was done to select homes for each of the three treatment groups and the remaining homes were automatically considered part of the control group. Table 3.5 shows the number of homes included in each treatment group and the control group and shows the total number of 601 homes.

<b>Treatment Group</b>	<b>Comparison Level</b>	<b>Initial Number of Homes</b>
1	Neighborhood	75
2	Street	75
3	Next-Door Neighbor	75
Control	-----	376
		<b>Total: 601</b>

**Table 3.5** Treatment and Control Groups for Home Energy Report Experiment

But homes still had to be randomly placed into these experiment groups. To accomplish this, each of the 601 eligible homes was assigned a random number between zero and one. The list of homes was then sorted by ascending random number and the first 75 homes were placed as members of the first experiment group, the “Neighborhood” level of comparison. The next 75 homes were placed as members of the second experiment group, the “Street” level of comparison. The next 75 homes were placed as members of the third experiment group, the “Next-Door Neighbor” level of comparison. The remaining 376 homes were placed as members of the control group.

The following list summarizes this process of randomly selecting homes to participate in the experiment.

1. Import June electricity usage data into master dataset of homes
2. Delete homes with no meters or faulty meters
3. Delete general officer quarters
4. Delete homes with projected moves during course of experiment
5. Assign random number to each remaining home
6. Sort in ascending order by random number
7. Place first 75 homes in “Neighborhood” comparison group

8. Place second 75 homes in “Street” comparison group
9. Place third 75 homes in “Next-Door Neighbor” comparison group
10. Place remaining 376 homes in control group

While 601 homes were initially considered as part of the experiment, this number decreased as the experiment progressed. This reduction in the number of homes was due to two reasons. First, even though households forecasted to move during the experiment were removed from the list of eligible homes, some additional households moved during the course of the experiment. This reduced the number of homes included, although not nearly to the degree it would have if the forecasted moves had not been initially removed. Second, during the last month of the experiment (September), the data provided no longer included electricity usage data for a batch of recently built homes. Presumably, some meter problems had developed with those homes, so they had to be removed from the usage data and, consequently, the experiment. The homes removed for this were evenly spread through the different experiment groups.

By the end of the experiment, 475 homes remained as eligible for analysis. These homes persisted through the duration of the experiment with the same occupants and functioning meters. Table 3.6 provides the initial and final numbers of homes involved in the experiment, broken down by experiment group.

<b>Treatment Group</b>	<b>Comparison Level</b>	<b>Initial Number of Homes</b>	<b>Final Number of Homes</b>
1	Neighborhood	75	58
2	Street	75	60
3	Next-Door Neighbor	75	63
Control	-----	376	294
		<b>Total: 601</b>	<b>Total: 475</b>

**Table 3.6** Initial and Final Number of Homes in Experiment

It should also be noted that just because a home was removed from the dataset of homes eligible for analysis in the experiment, they were not necessarily excluded from the experiment altogether. They were still necessary for the sake of comparing the electricity consumption of treatment homes via the home energy reports. This clarification applies only to the homes that were removed from the list of eligible homes due to a lack of consistent occupancy throughout the experiment. If a home had only partial occupancy during a particular month because the occupants switched out, the home was removed from inclusion in the treatment or control groups. However, if that home had full occupancy during the following month, its electricity usage for that month would be included in calculating the average electricity usage for its neighborhood and street. It would also be included in calculating the next-door neighbor average electricity usage if it was within two occupied homes of one of the treatment homes in that comparison category. So, essentially, while the homes of projected movers and actual movers were not eligible for inclusion in the treatment and control groups, any home that had full occupancy for any given month of the experiment was still included in the calculations of average electricity usage for that month, whether at the neighborhood, street, or next-door neighbor level.

### 3.3.2 Generation and Mailing of Home Energy Reports

The monthly electricity usage data and occupancy data was provided by the housing office at Joint Base Andrews. Once this data was received, it would take three to four days to generate and mail the home energy reports for that month. The process began with removing households from the dataset that moved out during the month and adding



back into the dataset households that had moved in during the previous month. Then, the electricity usage data was imported into the dataset and the average electricity usages for each neighborhood and street on the base were calculated. Also, the average electricity usages of the most efficient 20% of households in each neighborhood and on each street were calculated. For the next-door neighbor calculations, the maps of the base were referenced to determine the nearest two occupied homes on each side of each home in the “Next-Door Neighbor” comparison category, and the average electricity usage of these four homes was calculated.

All these averages were used in the generation of the customized home energy reports for all of the treatment households. Each report was individually generated by entering into a Microsoft Excel file the values for: the treatment household’s electricity usage for that month, the average electricity usage of the neighborhood or street, and the average electricity usage of the most efficient 20% of households in the neighborhood or on the street. The file would then create a horizontal bar chart that was cut and pasted into a Microsoft Word file. There were nine different such Microsoft Word files, one for each of the possible combinations of comparison categories and performance categories, as previously shown in Figure 3.5. Once the bar chart was inserted, the customization of the report was finalized by including the address at the top and updating a sentence near the top of the report that stated the household’s electricity usage as a percentage above or below other neighbors. If the household was a “Great” performer, the sentence stated the percentage of electricity consumed below the average of the most efficient neighbors in the comparison group. If the household was a “Good” performer, the sentence stated the

percentage of electricity consumed above the most efficient neighbors in the comparison group. If the household was a “More than Average” performer, the sentence stated the percentage of electricity consumed above all neighbors in the comparison group.

Once all the reports were generated, they were printed in color. The cover letter for that month was updated and printed in color as well. Then the mailings were stuffed into the envelopes. The address for each report was printed on the back of the report itself so that when folded it would display through the window on the envelope.

The June data was used to generate the June home energy reports, which were mailed on July 13. The July data was used to generate the July home energy reports, which were mailed on August 24. The August data was used to generate the August home energy reports, which were mailed on September 18. Unfortunately, none of the mailings were able to go out during the first few days of the month. For the first mailing, this was due mostly to working out the details of generating the reports for the first time. For the second and third mailings, which were mailed even further into the month, this was due to delays in receiving the data, which were the results of a transition in leadership at the housing office at Joint Base Andrews. These delays do not impact the ability of the experiment results to answer the research questions. The fact that the mailings did not get out earlier in the month simply means that the analysis should not interpret differences from month to month as being significant because the time after treatment varied from month to month. The analysis should focus on the cumulative impact of all three mailings across the different treatment groups.

## Chapter 4: Home Energy Report Experiment Results and Analysis

The home energy report experiment, as described in the previous chapter, allows us to test two different variations of the normative feedback model. First, we are interested in determining whether normative feedback for residential energy consumption will still produce energy savings even when the residents are not billed for their energy consumption. Second, we are interested in determining whether increasing the proximity of the comparison group from neighborhood, to street, to next-door neighbor, will create significant differences in energy savings. This chapter will analyze the results of the experiment and then interpret those results in relation to these two variations of the normative feedback model.

### 4.1 Experiment Results

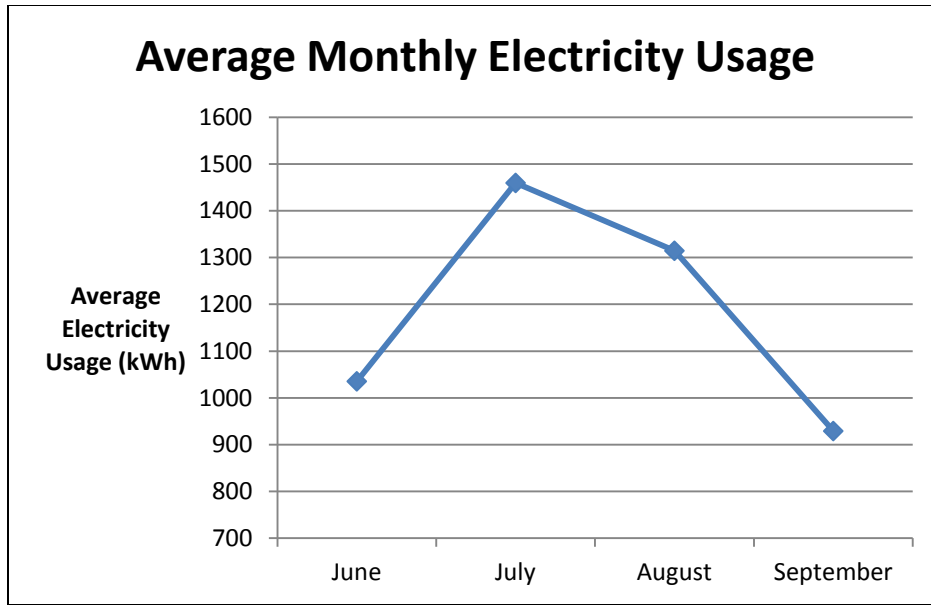
The home energy report experiment was conducted from June through September of 2012 at Joint Base Andrews in Maryland. It involved mailing customized home energy reports to 225 treatment households. As anticipated, by the end of the experiment, due to moves and some faulty meters, there remained 181 treatment households. The control group decreased in size from 376 to 294 for the same reasons. The treatment homes received home energy reports specific to one of the three treatment categories, which varied in terms of the level of comparison contained in the report. Because the experiment involved three rounds of mailings, it generated three sets of observations on each household included in the experiment. These observations consisted of electricity usage data for the months of July, August, and September. Table 4.1 shows the total number of observations in each experiment category over the course of those three

months. It should be noted that the only observations that are counted here and that will be analyzed in this research are from those homes that had consistent occupancy and functioning meters throughout the entire experiment. If the occupants of a particular home, whether in a treatment category or the control group, moved during the course of the experiment, any previous observations on that home were removed from the analysis.

<b>Treatment Group</b>	<b>Comparison Level</b>	<b>Initial Number of Homes</b>	<b>Final Number of Homes</b>	<b>Number of Observations</b>
1	Neighborhood	75	58	174
2	Street	75	60	180
3	Next-Door Neighbor	75	63	189
Control	-----	376	294	882
		<b>Total: 601</b>	<b>Total: 475</b>	<b>Total: 1,425</b>

**Table 4.1** Total Number of Observations Over Three Months

Before investigating differences between treatment groups, we want to get a general idea of the energy consumption behavior of the residents of Joint Base Andrews during the experiment. Focusing on the 475 homes with enduring occupancy throughout the four months of the experiment, we can generate the graph in Figure 4.1, which shows average electricity usage by month.



**Figure 4.1** Impact of Weather on Monthly Electricity Consumption

This chart gives us an idea of the range of electricity consumption by the households involved in the experiment. It also shows us that variations in weather make a significant impact on electricity consumption. In the summer of 2012, July was a remarkably hot month, and the associated increase in the use of air conditioning and increase in electricity consumption is evident on the chart. And as the weather began cooling off into September, the electricity consumption began to decline. Of course, if the experiment carried on into the winter and if we were monitoring overall energy consumption to include natural gas, we would see the energy consumption begin to rise again as the autumn weather transitioned to winter weather and residents would put their furnaces into increasing levels of service.

The important issue, however, for this research is the difference between categories of comparison. Figure 4.1 intermingles all the households in the experiment to include

treatment and control households, and it includes all the time periods in the experiment to include pre-treatment (June) and post-treatment (July through September). These distinctions must be sorted out and analyzed in order to determine the impact of the home energy reports across the different treatment groups, and in so doing to test our hypotheses.

While the quantification of the weather impact will be discussed in more detail further along in this chapter, it is important at this point to address the ability of a controlled, randomized experiment to account for the variations in weather that naturally occurred during the course of the home energy report experiment. The weather variations could lead to complications in analyzing the difference between pre-treatment and post-treatment observations, because of the huge impact weather has on monthly electricity consumption. The important aspect of the home energy report experiment that solves this problem is the existence of the control group. The households in the control group and in the treatment groups are all subject to the same weather each month. So, by analyzing the differences in electricity consumption between the control group and the treatment groups, we should be able to determine the impact of the treatment, distinct from the impact of the weather, in any of the treatment months (July through September). This method of analysis is displayed in Table 4.2.

Average Electricity Consumption (kWh)						
Experiment Group	July	August	September	Overall	Average Electricity Savings (kWh)	Average Electricity Savings (%)
Neighborhood	$\mu_{N1}$	$\mu_{N2}$	$\mu_{N3}$	$\mu_N$	$\mu_C - \mu_N$	$(\mu_C - \mu_N)/\mu_C$
Street	$\mu_{S1}$	$\mu_{S2}$	$\mu_{S3}$	$\mu_S$	$\mu_C - \mu_S$	$(\mu_C - \mu_S)/\mu_C$
Next Door Neighbors	$\mu_{ND1}$	$\mu_{ND2}$	$\mu_{ND3}$	$\mu_{ND}$	$\mu_C - \mu_{ND}$	$(\mu_C - \mu_{ND})/\mu_C$
Control	$\mu_{C1}$	$\mu_{C2}$	$\mu_{C3}$	$\mu_C$	---	---

**Table 4.2** Calculation of Average Energy Savings

The other important aspect of this type of controlled experiment is that the households have to be randomly divided between the treatment and control groups. This ensures that there are no inherent characteristics in any particular group that incline it to behave differently than other groups in terms of electricity consumption. Such inherent characteristics, if not accounted for, can bias the experiment one way or the other, distorting the results, and leading to inaccurate conclusions. For these reasons, the households in the home energy report experiment were placed into treatment and control groups in a random process, described in Chapter 3. It was expected that this randomization would avoid inherent differences between groups, and that the equality of the groups would be evidenced by equal, or close to equal, electricity consumption across all three treatment groups and the control group during the pre-treatment month (June). As will be shown, this pre-treatment equality was not as strong as would have been

desirable, so the simple analysis of Table 4.2 will not suffice, and it will be important to conduct the analysis in a way that takes any pre-treatment differences into account.

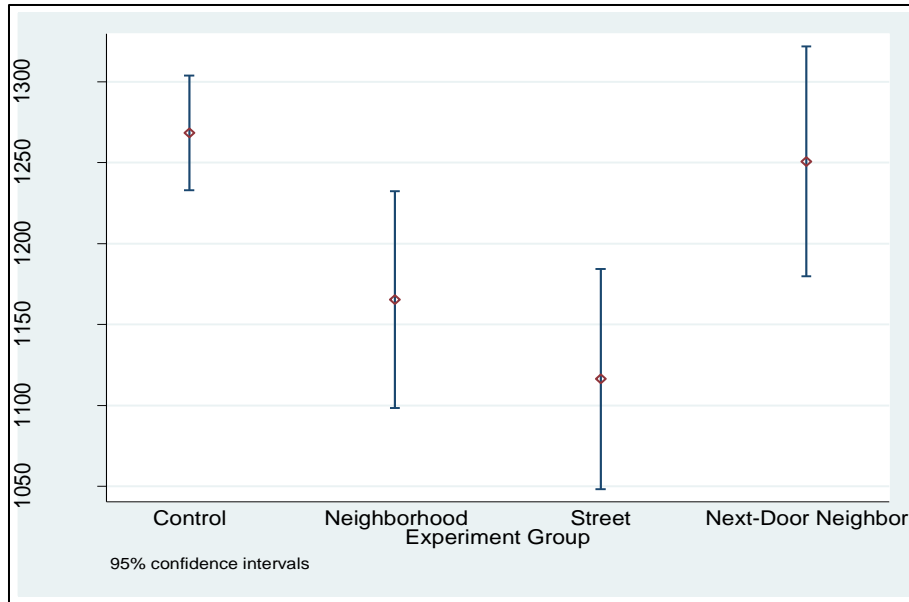
We should first examine the raw values of average electricity usage for each month by each experiment group. Table 4.3 provides these basic results.

Experiment Group	Number of Homes	Post-Treatment Months				Post-Treatment Average (kWh)
		June Average (kWh)	July Average (kWh)	August Average (kWh)	September Average (kWh)	
Neighborhood	58	1004	1422	1213	861	1165
Street	60	955	1336	1210	804	1116
Next-Door Neighbor	63	1066	1466	1330	957	1251
Control	294	1051	1491	1353	962	1268

**Table 4.3** Average Monthly Electricity Usage by Experiment Group

If we were to analyze only the post-treatment months and calculate savings based simply on the differences between the average electricity usages of the different treatment groups compared to the control group, we would want to examine a chart that includes confidence intervals such as the one in Figure 4.2.





**Figure 4.2** Post-Treatment Average Monthly Electricity Usage by Experiment Group

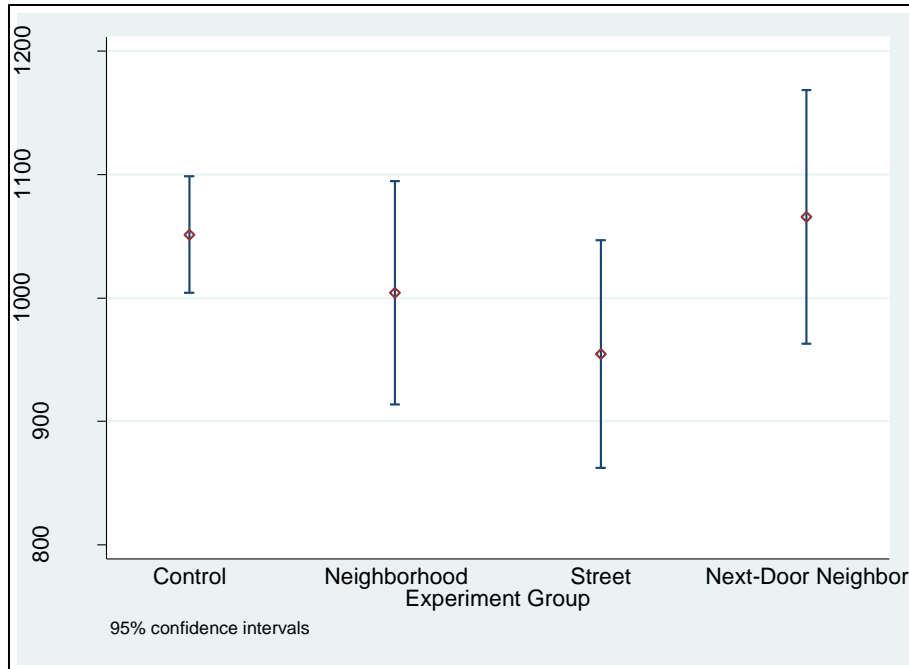
Examining this chart alone, we see that the average monthly electricity usage of the “Neighborhood” and “Street” level comparisons was significantly lower than the average monthly electricity usage of the control group during the three months after treatment began (July through September). We could conclude that the home energy reports had a significant impact when their comparisons of electricity consumption were made at the “Neighborhood” and “Street” level, with the “Street” level generating the most savings. We could also conclude that the comparisons made at the “Next-Door Neighbor” level did not have a significant impact, with the electricity usage of that treatment group being almost the same as that of the control group. A statistical analysis of these observations is shown in Table 4.4.

<b>Experiment Group</b>	<b>Number of Homes</b>	<b>Number of Post-Treatment Observations</b>	<b>Post-Treatment Average (kWh)</b>	<b>Standard Deviation</b>	<b>Savings (kWh)</b>	<b>Savings (%)</b>	<b>P-Value</b>
<b>Neighborhood</b>	58	174	1165	447	103	8.12%	0.0081
<b>Street</b>	60	180	1116	463	152	11.98%	0.0001
<b>Next-Door Neighbor</b>	63	189	1251	495	18	1.39%	0.6750
<b>Control</b>	294	882	1268	535	---	---	---

**Table 4.4** Average Electricity Savings by Experiment Group

The *P*-Values shown resulted from two-tailed, two-sample t-test procedures comparing each treatment group to the control group. The statistical significance indicated by these results is consistent with the confidence intervals shown on the chart in Figure 4.2. This analysis would indicate a significant savings of almost 12% from comparisons made at the “Street” level, a significant savings of just over 8% at the “Neighborhood” level, and a non-significant savings of over 1% produced at the “Next-Door Neighbor” level. But these conclusions assume that the randomization process in which the households were separated into the different treatment and control groups succeeded in establishing experiment groups with equivalent electricity usages during the pre-treatment time period. To determine whether this was the case or not, we need to examine the average electricity usage of each experiment group during the pre-treatment month of June.

Figure 4.3 provides the chart we need.



**Figure 4.3** Pre-Treatment Average Monthly Electricity Usage by Experiment Group

This chart could be interpreted in one of two ways. It could be concluded that no significant differences existed between the experiment groups during the pre-treatment month, and therefore we do not need to consider the pre-treatment data in our analysis of energy savings. We can simply use the post-treatment data to compare the treatment groups to the control group and calculate the savings associated with each treatment group, as we did in Table 4.4. However, the more conservative approach would be to recognize that differences do indeed exist in the pre-treatment electricity usage of the experiment groups. While these differences may not be statistically significant, they still suggest the existence of inherent differences between the groups in terms of electricity consumption characteristics. The next section provides a more thorough analysis of the results of the home energy report experiment by taking these pre-treatment differences into account.

## 4.2 Analysis of Results

This section builds on the initial analysis begun in the previous section by determining the amount of electricity savings for each treatment category, while taking into consideration the pre-treatment differences in electricity consumption that existed between the experiment groups. This will be accomplished through two approaches. The first will be through a differences-in-differences analysis and the second will be through a regression analysis. Both approaches will essentially consider the electricity usage of the pre-treatment month (June) as a baseline from which to measure changes resulting from the home energy report experiment. The results of both approaches will be presented together at the end of this section, and they should provide a more complete understanding of whether the different treatment categories generated different levels of electricity savings.

### 4.2.1 Differences-in-Differences Analysis

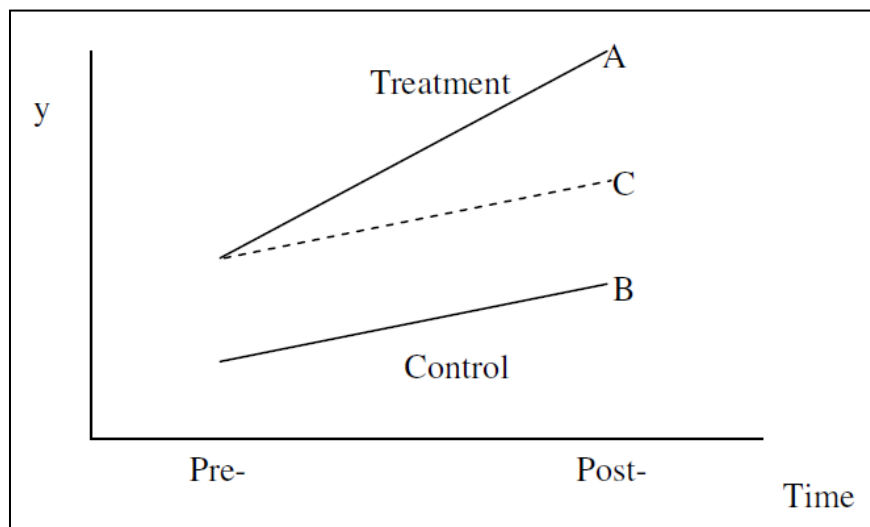
A controlled experiment has the potential of eliminating pre-treatment differences between experiment groups. In the case of our home energy report experiment, however, the randomization did not succeed in establishing experiment groups with equal, or very close to equal, electricity consumption. So we need a method of analysis that can handle the fact that each experiment group had a different starting point, or baseline, going into the experiment. A differences-in-differences approach allows us to do that.

The differences-in-differences approach requires us to make one reasonable assumption. If the experiment groups demonstrated different electricity consumptions during the pre-treatment month of June, these differences resulted from a number of unobserved

differences. These differences in human behaviors, orientation of the homes, sizes of the homes, floorplans, and unit types all contribute to the differences in electricity consumption. In order to use the differences-in-differences approach, we must assume that, in absence of any treatment, these unobserved differences would remain the same over time (Manning, 2012). This assumption is clearly valid for all the physical differences related to the homes themselves, as the homes included in each experiment group do not change throughout the course of the experiment. And with regard to behavioral differences between the groups, the assumption is quite reasonable, because the occupants also remain the same throughout the course of the experiment. It is reasonable to assume that their energy consumption behaviors would remain the same in the absence of treatment.

An explanation of the differences-in-differences approach will make clear the necessity of the assumption we have just made. For the sake of simplicity, we will briefly discuss just one hypothetical treatment group and compare it to a control group. The difference between the treatment group and the control group during the pre-treatment time period, in terms of the variable of interest, can be considered the “normal” difference between the two groups. This “normal” difference is the result of inherent differences between the two groups. Assuming this “normal” difference would remain constant in the absence of treatment, as discussed in the previous paragraph, we can compare it with the difference observed after treatment to give us the change in the variable of interest that is due only to the impact of the treatment. The graph in Figure 4.4 helps to clarify the approach. If the analysis were being conducted with only post-treatment data, one would simply

consider the distance AB as the treatment effect. However, given that a pre-treatment difference exists between the treatment and control groups, we can project that difference, represented by the distance CB, into the post-treatment time period. Then, subtracting the distance CB from the distance AB yields the actual treatment effect (Manning, 2012). This differences-in-differences approach essentially subtracts the pre-treatment difference from the post-treatment difference to determine the treatment effect.



**Figure 4.4** The Differences-in-Differences Approach (Manning, 2012)

Applying this approach to the home energy report experiment, we begin by calculating the difference between the pre-treatment electricity usage and the post-treatment electricity usage for each household. By examining each household and then folding the results together, we can obtain the average difference between pre- and post-treatment electricity usages for each experiment category. Then we can compare each treatment category to the control category, calculating the difference in that direction to get the results we need. We begin with the raw values for monthly electricity consumption from

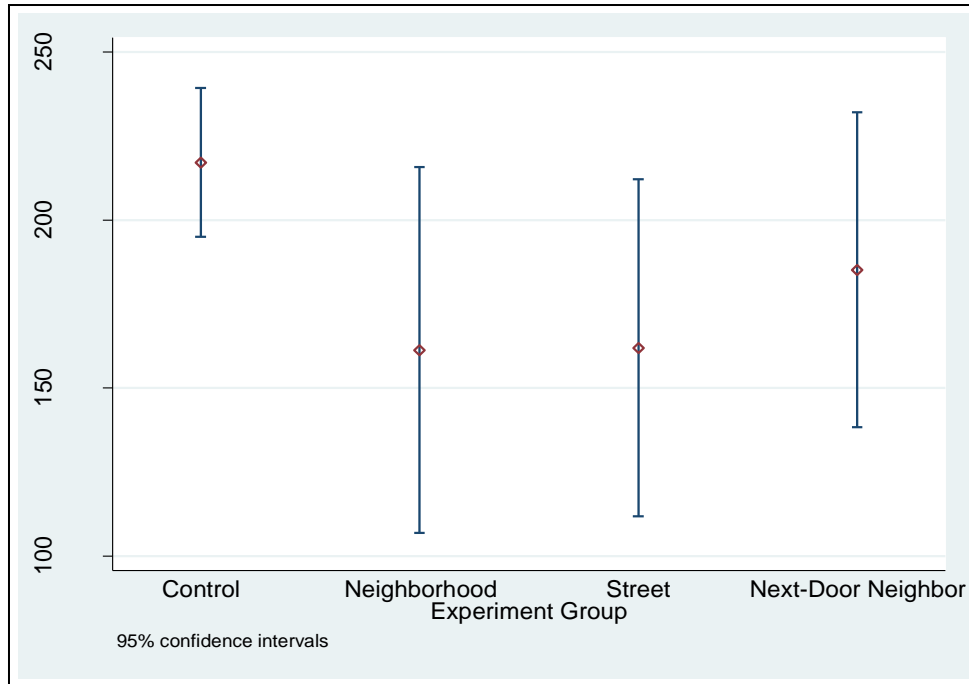
Table 4.3. A revised version of that table that calculates the average change in electricity consumption from the pre-treatment period of June is shown in Table 4.5.

Experiment Group	Number of Homes	Difference From Pre-Treatment Month of June			
		July Average Difference (kWh)	August Average Difference (kWh)	September Average Difference (kWh)	Overall Average Difference (kWh)
<b>Neighborhood</b>	58	418	209	-143	161
<b>Street</b>	60	381	255	-151	162
<b>Next-Door Neighbor</b>	63	400	264	-109	185
<b>Control</b>	294	440	302	-89	217

**Table 4.5** Differences Between Pre- and Post-Treatment Electricity Consumption

Note that there is now no column for June data. This is because the June consumption values have been subtracted from the consumption values for each of the treatment months. From the table above, we notice again that July was a particularly hot month during the summer of 2012, as indicated by the large increase in electricity consumption compared to the month of June. September represents the coolest month of the experiment as the electricity usage during that month fell below the electricity usage during June, and this is reflected in the negative values in the Table 4.5.

To help visualize this information and attach confidence intervals to the analysis, Figure 4.5 is provided.



**Figure 4.5** Difference Between Pre- and Post-Treatment Electricity Consumption

We can now reference Table 4.5 in calculating the differences-in-differences by subtracting the difference between pre-and post-treatment electricity usage for each *treatment* group from 217 kWh, which is the difference between pre- and post-treatment electricity usage for the *control* group. This calculation and the associated statistical analysis are shown below in Table 4.6.

Comparison Level	Number of Observations	Difference Between Pre- and Post Treatment (kWh)	Standard Deviation	Differences-in-Differences (kWh)	Savings	P-Value
Neighborhood	174	161	364	55.8	4.5%	0.0480
Street	180	162	341	55.2	4.5%	0.0450
Next Door Neighbor	189	185	327	32.0	2.6%	0.2325
Control	882	217	335	---	---	---

**Table 4.6** Differences-in-Differences Calculation of Electricity Savings



The values for savings in the above table were calculated by comparing the differences-in-differences for each treatment category to the average electricity usage for all households during the three months of treatment, which was 1,234 kWh. This value was used instead of the average electricity usage of just the control group because of the differing pre-treatment consumptions values already discussed. That is, if the consumption levels of the control group were inherently higher than the treatment groups, it does not make sense to account for that through the differences-in-differences analysis, but then use the control group average alone to calculate resulting savings. It makes more sense to use the average electricity consumption of all homes involved in the experiment, both treatment and control. The *P*-Values in the above table were generated through two-sided t-tests that compared the difference between pre- and post-treatment for each treatment category to the difference between pre- and post-treatment for the control category, using the associated number of observations and standard deviations. It should be noted that no statistically significant differences existed in the savings between the three treatment groups.

These results demonstrate a similar pattern to the previous results reported in Table 4.4, when we only analyzed the post-treatment electricity usage. Now that we have accounted for the differences in pre-treatment electricity usage, we see that once again, the “Neighborhood” and “Street” levels of comparison generated significant amounts of savings, while the “Next-Door Neighbor” level of comparison did not. However, the amount of savings generated by both the “Neighborhood” and “Street” levels of comparison has decreased substantially, down to 4.5%. This percentage of savings is

more consistent with that typically found in the literature related to changes in energy consumption behaviors. We also no longer see a distinction in the amount of savings generated between the “Neighborhood” and “Street” levels, whereas before, the “Street” level of comparison generated higher savings.

#### 4.2.2 Regression Analysis

The differences-in-differences analysis allowed us to calculate the electricity savings associated with each treatment category, while taking into consideration the pre-treatment differences. But we may be able to further improve the analysis. The pre-treatment differences in electricity consumption reflect the existence of inherent differences between the experiment groups in terms of energy consumption behaviors, sizes of the homes, neighborhoods, and unit types. A regression analysis will allow us to analyze the treatment impact while controlling for some of these inherent differences between experiment categories, not just in terms of their pre-treatment existence, but also in terms of their influence throughout the treatment months. It will also allow us to control for the monthly variations in weather that occurred throughout the experiment.

##### 4.2.2.1 Identifying the Dependent Variable

The first step in the regression analysis is to determine the dependent and independent variables. The dependent variable will need to be a measure of electricity usage and will need to account for the differences in pre-treatment usage. Accordingly, we will use the monthly difference from June electricity consumption for each household as our dependent variable. By accounting for pre-treatment differences in this way, we can

proceed with the regression analysis, focusing especially on the post-treatment differences in electricity consumption between treatment groups and the control group, having already accounted for the differences in pre-treatment consumption. This dependent variable can be calculated simply by subtracting the June electricity usage for each house from that house's electricity usage in each of the treatment months. This results in three observations for each household in the experiment, one for each of the three treatment months (July through September).

Using this "Difference from June" as our dependent variable reflects an interest not in controlling for how the independent variables caused the differences in *pre*-treatment consumption, but in how those variables caused differences in *post*-treatment consumption. This is why the regression analysis is needed – to control for the ways in which other factors besides the home energy reports influenced the observed changes in electricity consumption during the course of the experiment. Some of these factors, such as home size, might have different mechanisms for influencing the change in consumption, and those different mechanisms might even have somewhat off-setting influences. For instance, the increase in electricity consumption by a larger home during a hot month will be more than the associated increase by a smaller home. But, if the occupants of a larger home make efforts to conserve energy and lower their thermostat, they can generate a higher quantity of electricity savings than can the occupants of a smaller home who make an identical thermostat adjustment. So, a particular larger home could experience these off-setting influences in any given month. The point of this regression analysis is not to parse out how these different mechanisms might be

influencing changes in electricity consumption, but rather to identify the influencing variables and control for them. This will allow us to see more clearly the impact of the home energy reports without the varying compositions of the experiment groups clouding the picture.

Having identified the dependent variable, we now need to take a look at the basic statistical descriptives of the dependent variable. Table 4.7 provides these descriptives for “Difference from June” for each of the three treatment months. It is evident that, as we have noted previously, weather has a dominating impact. We see that the average electricity usage in July, the hottest month of the experiment, was 424 kWh higher than the average electricity usage in June. We see that the average electricity usage in September, the coolest month of the experiment, was 106 kWh lower than the average electricity usage in June.

Month	Number of Observations	Difference from June Electricity Usage (kWh)			
		Mean	Standard Deviation	Minimum Value	Maximum Value
July	475	424	263	-741	1586
August	475	279	251	-860	1288
September	475	-106	250	-1480	1130
Overall	1425	199	339	-1480	1586

**Table 4.7** Difference from June Electricity Usage by Month

#### 4.2.2.2 Identifying the Independent Variables

In identifying the independent variables for the regression analysis, two primary criteria were used. First, each independent variable needed to have a likelihood of influencing

the dependent variable of “Difference from June.” This is standard for any regression analysis. In this case, we needed to identify those variables that would impact not necessarily the monthly electricity usage of a household, but more particularly, the change in the household’s electricity usage as compared to the baseline month of June. And second, the variables needed to vary in their values or amounts across the different experiment groups. This connects to the purpose of running this regression analysis. That is, we are interested in controlling for variables that may not be equally represented in the different experiment groups in order to make a more accurate assessment of the impact of the different home energy reports.

So, what variables meet these criteria to be included in the regression analysis? In a broad sense, the physical features of the house itself, the occupants within the house, and the weather, all influence the monthly electricity consumption of the house and may exist in variation across the different experiment groups. The ensuing paragraphs will step through each of the independent variables that will be used in the regression analysis.

The physical features of the house, such as its size and whether it is a single family home, a duplex, or a townhome, significantly influence how much electricity is used in the home, particularly how much energy is required to heat or cool the home. More to the point of this regression analysis, however, the physical features influence the amount of electricity savings that a household can generate during a given month. The first physical feature of the house to be included as an independent variable in the regression analysis is the home size. Any difference between the experiment groups in terms of average home

size should have an impact on the average electricity usage of that experiment group, because bigger homes require more electricity to cool during the summer months.

We also need to examine whether home size exists in variation across the different experiment groups. Table 4.8 shows the average home sizes in square feet along with the standard deviation for each experiment category.

<b>Experiment Group</b>	<b>Number of Homes</b>	<b>Average Square Footage</b>	<b>Standard Deviation</b>
Neighborhood	58	1645	393
Street	60	1622	357
Next-Door Neighbor	63	1695	439
Control	294	1642	418

**Table 4.8** Variation in Average Home Size across Experiment Groups

From this table, we clearly see the existence of differences in home size between the groups. The “Next-Door Neighbor” category of comparison contained the largest home sizes, being on average 73 square feet larger than the homes in the “Street” category of comparison, which contained the smallest home sizes. This represents more than a 4% difference in home size. The other two experiment groups are in the middle of the range and quite comparable to each other.

The second physical feature of the home that impacts changes in energy consumption is the unit type. This refers to whether the home is a single family home, a duplex, or a townhouse. The bigger the home, the more energy is required to heat it or cool it. And a home that is connected to other homes, such as in a duplex or townhome unit, will not require as much energy to heat or cool, because the connecting units will act as

insulation, reducing the number of sides of the home that are exposed to the outdoor temperatures. End-unit townhouses are considered as duplexes in this analysis, because the relevance of considering unit type as an independent variable has to do with how many sides of the home are exposed to the outdoor elements. Put more precisely, out of the four sides of a standard home, if all four sides are exposed, the home was considered a single family home. If three sides were exposed, it was considered a duplex, so this would include townhouse end-units. And if only two sides were exposed, it was considered a townhouse.

To evaluate the inclusion of unit type as an independent variable in the regression analysis, Table 4.9 below provides the average “Difference from June” electricity usage for each of the three unit types.

<b>Unit Type</b>	<b>Number of Observations</b>	<b>Average Difference from June Electricity Usage (kWh)</b>	<b>Standard Deviation</b>
Townhouse	261	187	349
Duplex	969	196	322
Single Family	195	232	401

**Table 4.9** Difference from June Electricity Usage by Unit Type

This table shows that the single family units used, on average, 232 kWh more electricity each month as compared to the amount of electricity those same single family units used in the baseline month of June. This difference is 36 kWh more than the difference observed in the duplex unit types and 45 kWh more than the difference observed in the

townhouse unit types. So, we observe that the unit type of a household seems to have influenced the changes in that household’s electricity consumption over the course of the home energy report experiment.

We also need to examine whether unit type is a factor that varies across the experiment groups in terms of their composition. Table 4.10 breaks down the differences between the experiment groups by unit type, providing the number of homes in each experiment group that are classified into each of the three different unit types.

Experiment Group	Total Number of Homes	Unit Type					
		Townhome		Duplex/End Unit		Single Family Home	
		Number	%	Number	%	Number	%
Neighborhood	58	14	24.1%	36	62.1%	8	13.8%
Street	60	14	23.3%	38	63.3%	8	13.3%
Next-Door Neighbor	63	10	15.9%	44	69.8%	9	14.3%
Control	294	49	16.7%	205	69.7%	40	13.6%

**Table 4.10** Variation in Unit Type across Experiment Groups

In this simplified version of a frequency table, we see a good distribution of single family homes amongst the four experiment groups, with each of the groups comprised of between 13-14% single family homes. However, with the other two unit types, the distribution is not as good, though no alarming problems are observed. The “Neighborhood” and “Street” level experiment groups contain a higher percentage of townhomes than duplexes, and the “Next-Door Neighbor” level and control group contain a higher percentage of duplexes than townhomes.



Another independent variable we need to include in the regression analysis is the neighborhood in which each house resides. The neighborhoods on Joint Base Andrews are established based on the rank of the occupants. Senior officers live in one neighborhood; junior officers in another. Senior non-commissioned officers live in one neighborhood; junior non-commissioned officers live in another. Table 4.11 shows how the neighborhoods on Joint Base Andrews are broken down by rank, with “O” being the standard designation in the military for commissioned officers, and “E” being the standard designation for enlisted members. The associated numbers represent levels of rank within either the officer or enlisted rank structure.

<b>Neighborhood</b>	<b>Rank</b>
Adams Circle	O4-O5
Airey Court	E9
Cleveland Square	Unaccompanied
Fairway Drive	E8-E9
Jefferson Village	E5-E8/O3-O5
Lincoln Place	E5-E8
Madison Cove	E5-E8
Monroe Gardens	E5-E6
Roosevelt Court	E5-E8
Truman Place	Unaccompanied
Wilson Square	E5-E6

**Table 4.11** Breakdown of Neighborhoods on Joint Base Andrews by Rank

This table demonstrates that each neighborhood has a somewhat unique makeup of residents, in terms of rank. Some neighborhoods contain residents within a fairly tight band of rank, while others have a more inclusive range. Some, such as Jefferson Village,

contain both officers and enlisted, though in different sections within the neighborhood. The “Unaccompanied” neighborhoods are for residents who are not accompanied by a family, and will likely have different energy consumption characteristics than the other neighborhoods that contain families. These neighborhoods also contain a mixture of ranks.

Now, to evaluate the appropriateness of including neighborhood as an independent variable in the regression analysis, Table 4.12 provides the average “Difference from June” electricity usage for each of the 11 neighborhoods.

<b>Neighborhood</b>	<b>Number of Observations</b>	<b>Average Difference From June Electricity Usage (kWh)</b>	<b>Standard Deviation</b>
Adams Circle	84	208	468
Airey Court	15	252	280
Cleveland Square	147	187	382
Fairway Drive	36	196	372
Jefferson Village	240	225	310
Lincoln Place	114	229	460
Madison Cove	6	274	363
Monroe Gardens	297	145	282
Roosevelt Court	327	184	266
Truman Place	33	292	372
Wilson Square	126	265	372

**Table 4.12** Difference from June Electricity Usage by Neighborhood

The values of the dependent variable, “Difference from June” range from 145 kWh in Monroe Gardens to 292 kWh in Truman Place. This represents slightly more than a

100% difference, providing reason for the regression analysis to include neighborhood as an independent variable that wields influence on the dependent variable.

But we also need to take a look at the amount of variation across the experiment groups with regard to this independent variable of neighborhood. Table 4.13 provides this information.

Experiment Group	Number of Homes	Neighborhood											
		Adams Circle		Airey Court		Cleveland Square		Fairway Drive		Jefferson Village		Lincoln Place	
		#	%	#	%	#	%	#	%	#	%	#	%
Neighborhood	58	4	6.9	0	0.0	6	10.3	3	5.2	10	17.2	5	8.6
Street	60	3	5.0	0	0.0	7	11.7	4	6.7	8	13.3	4	6.7
Next-Door Neighbor	63	5	7.9	1	1.6	7	11.1	0	0.0	12	19.0	7	11.1
Control	294	16	5.4	4	1.4	29	9.9	5	1.7	50	17.0	22	7.5
		Madison Cove		Monroe Gardens		Roosevelt Court		Truman Place		Wilson Square			
		#	%	#	%	#	%	#	%	#	%		
		0	0.0	15	25.9	11	19.0	0	19.0	4	0.0		
		0	0.0	10	16.7	15	25.0	1	25.0	8	1.7		
		0	0.0	10	15.9	14	15.9	2	22.2	5	3.2		
		2	0.7	64	21.8	69	21.8	8	23.5	25	2.7		

**Table 4.13** Variation in Neighborhood Composition across Experiment Groups

The most important thing to note about this table is that many of the neighborhoods are not evenly represented across the four experiment categories. Even one of the most populated neighborhoods, Monroe Gardens, makes up 25.9% of the “Neighborhood” group, but it makes up only 15.9% of the control group. These differences between

experiment groups further validate the inclusion of neighborhood as an independent variable in the regression analysis.

Beyond the homes and neighborhoods, the monthly variations in weather also influence the monthly electricity consumption. Some method of quantifying the monthly weather must be employed to generate an independent variable that will control for weather variations in the regression analysis. The use of cooling degree days (CDD) will accomplish this objective. A CDD is an indicating measure of how much cooling energy is required due to the weather during a given time period. The actual units of a CDD measurement are degree-days. For this research, the CDD calculations were made on a monthly basis to match the duration of time over which the electricity meters were read. The amount of CDDs in a given month is calculated one day at a time. For each day, the difference between the average daily temperature and the established base temperature is calculated. Typically, and in this research, 65° is used as the base temperature. This base temperature figures from assuming 75° as an ideal indoor air temperature and then subtracting 10° to account for internal heat gain. Once the difference between average daily temperature and the base temperature is calculated for each day of the month, those values are added together to establish the amount of CDDs for the month. These values for the four months of the home energy report experiment for Joint Base Andrews in Maryland are found in Table 4.14 (Weather Underground, 2012).

Month	CDD
June	346
July	595
August	501
September	229

**Table 4.14** Cooling Degree·Days During Experiment

This weather data needs to be included as an independent variable in the regression analysis because of its strong influence on the amount of electricity consumed by the homes, as shown previously in Figure 4.1.

The final independent variable that needs to be included in the regression analysis is the experiment group to which each household is assigned, which represents the variable of interest. This is the variable that will allow for conclusions to be drawn as to how the different categories of comparison in the home energy reports impacted energy consumption behavior in the experiment households.

#### 4.2.2.3 Regression Results

A regression analysis will help identify how each of these independent variables influences the dependent variable. Conducting a regression analysis that can handle a combination of continuous and categorical variables requires the use of sophisticated statistical analysis software, such as Stata. The Stata12 version is used in this analysis. Before dumping all the variables into a regression analysis, one final component must be considered, having to do with the occupants themselves. In all 475 houses the occupants remained the same throughout the duration of the experiment. This creates a correlation between each of the monthly electricity usage values of a given house, because the

behaviors and belongings of the occupants have a fairly consistent impact on the electricity usage from month to month. Even when a particular set of occupants attempts to change their energy consumption behavior, the amount of electricity saved is inevitably connected to their starting point as determined by the previous month's behavior. Therefore, the monthly usage values for each particular house need to be connected together in some way in the analysis. To accomplish this, the "cluster" option was employed in Stata as part of the regression command. A household identifier was assigned to each household, and the regression command included a "cluster by" option for the household identifier.

The results of the regression analysis are shown in Table 4.15. The actual Stata output is included as Appendix C. There are several initial observations about these results before getting into the variable of interest. We first note the r-squared value of 0.458. This tells us that the variables included in the regression account for almost half of the variation observed in the dependent variable. While in some disciplines this may seem low, it is reasonable that, when human behavior is involved, plenty of room for unexplained variation is expected. So many events and decisions in a given month can impact electricity consumption in a household: hosting a party, a new video game, a new baby, etc. These things cannot all be captured by the regression model.

<b>Independent Variable</b>	<b>Regression Coefficient</b>
House Size (ft <sup>2</sup> )	-0.12 (0.113)
Unit Type	
Townhouse	-----
Duplex	34.55 (0.270)
SFH	96.98 (0.055)
Neighborhood	
Adams Circle	-----
Airey Court	40.91 (0.502)
Cleveland Square	-111.26 (0.334)
Fairway Drive	-42.39 (0.702)
Jefferson Village	-62.55 (0.400)
Lincoln Place	-59.76 (0.535)
Madison Cove	-4.30 (0.974)
Monroe Gardens	-188.93 (0.096)
Roosevelt Court	-92.36 (0.294)
Truman Place	-14.63 (0.910)
Wilson Square	-26.51 (0.796)
CDD	1.44 (0.000)
Experiment Group	
Control	-----
Neighborhood	-46.95 (0.180)
Street	-60.34 (0.025)
Next-Door Neighbor	-34.69 (0.151)
Constant	-170.60 (0.403)

Note:  $r^2 = 0.458$ ; p-values in parentheses

**Figure 4.15** Regression Results for Home Energy Report Experiment

An interesting observation is that the variable “House Size” actually has a negative coefficient. It is important to remember that our dependent variable is not monthly electricity usage, but it is the “Difference from June” electricity usage. Going into the analysis, it was hard to predict whether this coefficient would end up positive or negative. As previously described, a larger household has, for example, more air to cool, but that also creates the possibility of more savings from thermostat reductions.

It should also be noted that the *P*-values for the neighborhood variable are not all statistically significant. However, this is due primarily to the low numbers of observations within most neighborhoods. The two largest neighborhoods, Roosevelt Court and Monroe Gardens, have the lowest *P*-values, and thus come the closest to obtaining significance. When an F-test is conducted on the variable of “Neighborhood,” the *P*-value comes out as .0091, indicating that this is a variable with a lot of explanatory power that should be included in the regression, even if each individual neighborhood lacks a significant *P*-value.

A final interesting note is that Monroe Gardens is the neighborhood with the lowest value of all the neighborhood coefficients. This neighborhood is comprised of junior non-commissioned officers. These are enlisted members who have typically been in the military for six to ten years. Adams Circle and Airey Court, on the other hand, are where the highest-ranking individuals live, and these neighborhoods have the highest coefficients, indicating a relatively higher electricity consumption during the treatment period.



The most important results associated with this regression analysis are the coefficients associated with the different experiment groups. The “Control” experiment group was given a value of zero in the dataset, so that the regression coefficients for the three treatment groups would automatically be relevant to the control group. In this analysis, we have indications of different levels of response between the “Neighborhood” level comparisons and the “Street” level comparisons. In the previous differences-in-differences analysis, we found an almost equal electricity savings of about 55 kWh for both of these experiment groups, and only about 32 kWh for the “Next-Door Neighbor” level of comparison, as displayed in Table 4.6. These regression results indicate that when we control for other influencing variables, we find that a difference does exist between the impact of the “Neighborhood” level comparisons and the “Street” level comparisons. In fact, we find that the “Neighborhood” experiment group lowered its electricity consumption by about 47 kWh more than the control group, and the “Street” experiment group lowered its electricity consumption by about 60 kWh more than the control group. It should be noted here that, when tested in a follow-on analysis, no statistically significant differences existed between the savings of the three treatment groups. And while the amount of savings in the “Neighborhood” and “Next-Door Neighbor” categories fall short of statistical significance, the amount of savings in the “Street” category obtains statistical significance with a *P*-value of 0.025. The regression analysis reveals these distinctions and helps separate out the impact of the different comparison levels in the home energy reports, particularly the difference between the “Neighborhood” and “Street” levels of comparison.

### 4.3 Interpretation of Results

In order to summarize the results from the preceding sections, Table 4.16 displays the results from both the differences-in-differences analysis and the regression analysis. The table presents the electricity savings experienced by each of the treatment groups in the experiment, along with the associated *P*-values to provide an indication of statistical significance. The calculation of savings percentage is based on a comparison to the average electricity usage during the entire three months of treatment, which was 1,234 kWh.

	Electricity Savings (kWh)		Savings Percentage		<i>P</i> -value	
	Differences in Differences	Regression	Differences in Differences	Regression	Differences in Differences	Regression
<b>Neighborhood</b>	55.8	47.0	4.5%	3.8%	0.0480	0.1800
<b>Street</b>	55.2	60.3	4.5%	4.9%	0.0450	0.0250
<b>Next-Door Neighbors</b>	32.0	34.7	2.6%	2.8%	0.2325	0.1510

**Table 4.16** Summary of Results from Differences-in-Differences and Regression Analyses

These results will be used to test the two hypotheses set forth in the preceding chapter. Those hypotheses correlate with two variations of the normative feedback model. The first variation involves the absence of financial incentives and the second variation involves altering the comparison level of the normative feedback.

#### 4.3.1 Variation 1: Normative Feedback in Absence of Billing System

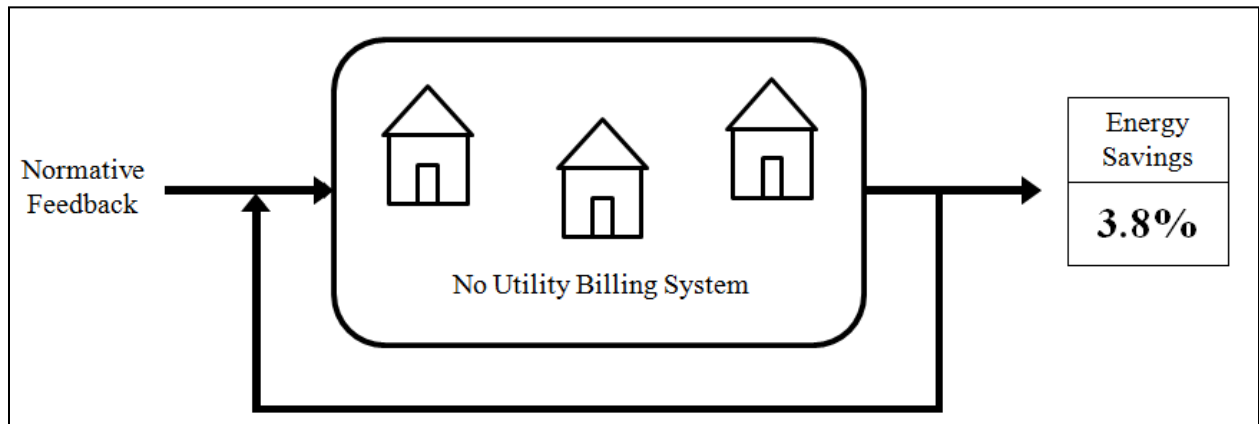
The first variation of the normative feedback model is designed to answer the research question of whether normative feedback can generative energy savings when applied in an environment in which no financial incentive exists for conservation. The neighborhoods on Joint Base Andrews are the ideal place to test this variation because no utility billing program currently exists, yet the homes are individually metered, allowing for measurement and feedback. The literature on normative feedback for energy conservation focuses exclusively on providing feedback to households who also receive regular utility bills. But the originating research in the field of social norms and normative feedback, particularly in the context of alcohol consumption, was conducted in settings where no such financial incentives were involved. Because of this, the hypothesis related to this first variation of the normative feedback model stated the following:

Hypothesis 1: Normative feedback on residential energy consumption will still produce positive energy savings even when residents have no financial incentive to conserve.

To put it more precisely in statistical terms, we could state the following, in which  $\mu_{\text{savings}}$  stands for the average savings of the treatment groups:

Null Hypothesis:	$\mu_{\text{savings}} = 0$
Hypothesis 1:	$\mu_{\text{savings}} > 0$

Figure 4.6 depicts the actual results from the home energy report experiment, which found electricity savings in the treatment groups of 3.8%. This overall percentage of savings was the same in both the differences-in-differences analysis and the regression analysis.



**Figure 4.6** Energy Savings of Normative Feedback in Absence of Billing System

Therefore, we accept our first hypothesis, as the home energy report demonstrated positive electricity savings for the treatment households on Joint Base Andrews.

This result validates the effectiveness of social norms as a tool to modify behavior even when no financial incentives or disincentives are associated with the normative feedback process. Furthermore, this result seems to indicate that it is the normative feedback, rather than associated monetary savings in utility expenditures, that are causing the savings generated by OPOWER's home energy reports. The residents of Joint Base Andrews who received the home energy reports had nothing to gain or lose financially by modifying their energy consumption behavior. While the responses of each household varied, with some households actually increasing their relative electricity usage, overall

the households that received the home energy reports modified their behavior and conserved electricity.

The implications of this extend beyond the field of social norms. Future applications of normative feedback for energy conservation should not hesitate to target facilities in which the occupants do not pay for utility consumption. This could include providing normative feedback to residents of college dormitories, apartment complexes, and even office buildings. More germane to this research, however, is the potential to extend this type of normative feedback throughout military family housing. The Department of Defense spends approximately 3.8 billion dollars in a year on facility energy, with 20% of those facilities being military family housing (Robyn, 2010). And even though the plan is to implement utility billing throughout military family housing, currently two-thirds do not have a billing program in place (Jowers, 2012). As a rough estimate, if home energy reports were implemented at these bases, and if this implementation resulted in 3.8% savings as experienced in this experiment, approximately 19.3 million dollars could be saved each year.

#### 4.3.2 Variation 2: Proximity Based Normative Feedback

The second variation of the normative feedback model varies the proximity of the normative feedback. That is, it varies whether households receiving normative feedback via home energy reports were compared to other households in their neighborhood, to other households on their street, or to their next-door neighbors. This variation was tested within the same home energy report experiment as was tested the first variation. As discussed in the literature review, previous studies have suggested that increasing the

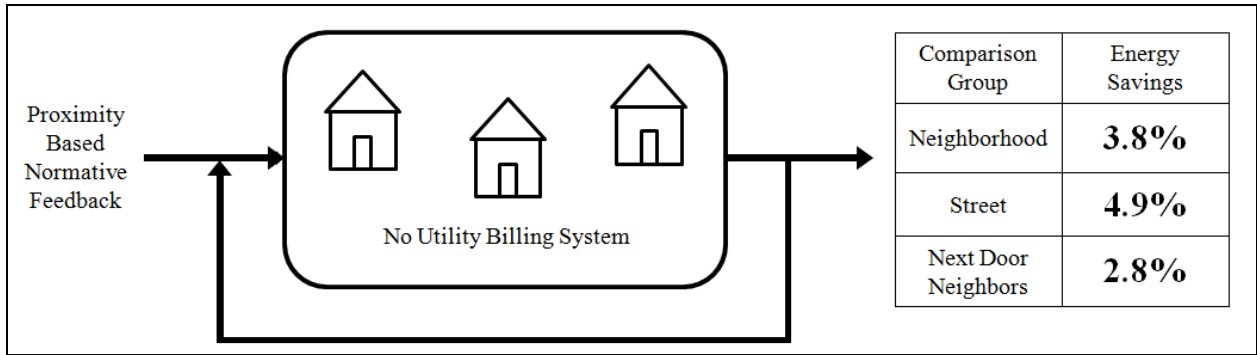
proximity of normative feedback will increase the impact of that feedback. Most prominently, a study employed normative feedback regarding hotel room towel reuse. Guests were more likely to reuse their towel when exposed to descriptive norms regarding the reuse rates of other guests who had stayed in the same room versus other guests in general (Goldstein, Cialdini, & Griskevicius, 2008). Extending this idea to the realm of energy conservation behaviors led to the formation of the second hypothesis. The second hypothesis stated the following:

Hypothesis 2: Increasing the comparison group proximity in normative feedback for residential energy consumption will increase the amount of energy savings.

Again, putting it more precisely in statistical terms, we could state the following, in which  $\mu_{N\text{savings}}$  stands for the electricity savings at the “Neighborhood” level of comparison,  $\mu_{S\text{savings}}$  stands for the electricity savings at the “Street” level of comparison, and a  $\mu_{ND\text{savings}}$  stands for the electricity savings at the “Next-Door Neighbor” level of comparison:

Null Hypothesis:	$\mu_{N\text{savings}} = \mu_{S\text{savings}} = \mu_{ND\text{savings}}$
Hypothesis 2:	$\mu_{N\text{savings}} < \mu_{S\text{savings}} < \mu_{ND\text{savings}}$

Figure 4.7 depicts the actual results from the home energy report experiment, broken down by comparison category. The percentages used are the ones resulting from the regression analysis, in which we controlled for other influencing factors on energy consumption, such as house size, unit type, neighborhood, and weather.



**Figure 4.7** Energy Savings of Proximity Based Normative Feedback

This is where we begin to have problems with our second hypothesis. These results seem to somewhat validate and somewhat invalidate the hypothesis that increasing the proximity of the comparison will increase the resulting savings. The “Street” level of comparison indeed increased the electricity savings, as compared to the “Neighborhood” level, increasing the savings from 3.8% to 4.9%. This is consistent with the hypothesis and seems to indicate that being compared to homes in closer proximity to one’s own home gives the socially normative information more strength. But if that were completely true, we would expect that the “Next-Door Neighbor” level, the closest proximity of comparison in this experiment, would yield the most savings. But instead of further increasing the savings, the “Next-Door Neighbor” level of comparison actually experienced the lowest savings of all three categories, with an electricity savings of just 2.8%.

This suggests that another dynamic is at work as the proximity of comparison increases to the next-door neighbor level. The results indicate that if the proximity of comparison gets too close, it weakens the impact of the normative feedback. This unexpected phenomenon can perhaps be explained with some help from the field of attribution

theory, which originated to explain the reasons and ways in which we try to make sense out of our own behaviors and the behaviors of others (Himmelfarb, 1974). In particular, actor-observer bias could play a role in mitigating the impact of the normative feedback when the proximity of comparison increased to the next-door neighbor level. Actor-observer bias is defined as the human tendency to interpret one's own actions as resulting from situational factors, and interpret the actions of others as resulting from dispositional factors. In this sense, when you are the "actor," you explain your own behavior in terms of the circumstances or situations that impacted the behavior. When you are the "observer," you explain another's behavior in terms of the personality or disposition of that person (Jones & Nisbett, 1971). Of particular significance to the interpretation of the experimental results, however, is that the manifestation of the actor-observer bias requires, of course, the opportunity to make observations of others. It is in this precondition that we find differentiation between the "Next-Door Neighbor" treatment group and the other treatment groups. It is with next-door neighbors that one has the most opportunities to make observations, and therefore the most likelihood of the actor-observer bias manifesting itself.

As an example, suppose you have a next-door neighbor and on a few different occasions he did not mow his grass until the blades were so high that cutting it left clumps of cut grass laying throughout his yard. You explain these observations by concluding that your neighbor is lazy and inconsiderate. You have interpreted your observations of your neighbor's behavior in terms of his disposition or personality. As for your own actions, you have also cut your grass late a time or two, but you explain your late grass-cutting by



citing your busy work schedule and sick children. You have interpreted your own actions in terms of your situation.

How would this actor-observer bias influence the response to the normative feedback contained in the home energy reports, particularly at the “Next-Door Neighbor” level? If you have made observations of your next-door neighbors and have explained their behaviors in ways that define their personality, you will be more likely to dismiss comparisons made to those neighbors. For instance, if you received a home energy report showing that your home consumed more electricity in the past month than the homes of your next-door neighbors, your mind might go fairly quickly to the neighbor who did not cut his grass. Receiving feedback that your neighbor’s household is outperforming your household in terms of energy efficiency would not fit with your conclusions of your neighbor’s laziness and lack of consideration. To accommodate the new information would require a paradigm shift in how you view your neighbor. This would reduce the likelihood of you receiving the feedback well. You may be inclined to dismiss the comparison and not alter your energy consuming behaviors.

This is, of course, a silly example, but it attempts to flesh out how the actor-observer bias could be the mechanism by which the “Next-Door Neighbor” level of comparison actually mitigates the electricity savings produced by the home energy reports, rather than further increasing them. The closer proximity of next-door neighbors leads to a higher frequency of observation. With more observations, the actor-observer bias strengthens, and the occupant explains the behaviors of next-door neighbors as resulting from their dispositions. This makes it easier to dismiss normative feedback, particularly

if it does not seem to align with the previous conclusions regarding the dispositions of the neighbors.

The results from the home energy report experiment indicate that the second hypothesis cannot be accepted without revision. While the second hypothesis is rejected as originally crafted, the following revised hypothesis is presented:

$$\text{Revised Hypothesis 2: } \mu_{\text{Nsavings}} < \mu_{\text{Ssavings}} > \mu_{\text{NDsavings}}$$

The implication of this portion of the research is that there exists a “sweet spot” in setting the proximity of comparisons in normative feedback. Future applications of normative feedback can increase the treatment effect by increasing the proximity of the comparisons. However, if the proximity gets too close, the treatment effect will diminish due to the actor-observer bias.

#### 4.4 Impact of Performance Categorization

An additional point of analysis in this experiment involves the boomerang effect described in the literature review. The boomerang effect describes the response to normative feedback exhibited by those who are already demonstrating the socially desirable behavior. For instance, in the case of home energy consumption, during the pre-treatment time period, households are demonstrating either: 1) higher than average energy consumption, 2) average energy consumption, or 3) lower than average energy consumption. It is this third group that is already performing in the desired manner – their energy consumption is low compared to the average. For this group, a problem can arise in the application of normative feedback. When these low-consumers receive

feedback on the energy consumption of their neighbors and realize their deviation from normative behavior, social norms theory would indicate that they may actually increase their energy consumption in order to more closely pattern their behavior after that of their neighbors. Obviously, this is not the intended effect of the normative feedback, and this is referred to as the boomerang effect.

As discussed in the literature review, other studies have demonstrated that the inclusion of injunctive norms with the normative feedback can eliminate this boomerang effect (Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007). Injunctive norms simply provide some sort of indication of social approval for the desired behavior and disapproval for the undesired behavior. However, these other studies, to include studies on the impact of OPOWER's use of normative feedback, have all occurred in environments in which households pay for their metered utility usage and thus have financial incentive to maintain low energy consumption. It is not known whether injunctive norms can eliminate the boomerang effect without the presence of such financial incentives. Because the research in this dissertation applied normative feedback through home energy reports that contained both descriptive and injunctive norms, it provides a unique opportunity to examine whether the boomerang effect can still be eliminated through the use of injunctive norms even when no financial incentive exists.

Such an analysis can be made by focusing attention especially on the group of homes that were designated by the performance category of "Great" during the pre-treatment month of June. We will conduct a differences-in-differences analysis to determine whether this group altered their energy consuming behaviors, measuring any resulting energy savings

or increases. We will actually conduct the analysis for all three performance groups, “Great,” “Good,” and “More Than Average,” but our focus will be on the interpretation of the results for the “Great” group, as that is the group that would be inclined to demonstrate the boomerang effect.

Because a household’s performance designation can change from month to month, it is only possible to analyze changes demonstrated between the pre-treatment month of June and the first month of treatment, which was July. Besides the fact the performance designations shift from month to month, another complicating factor is the timing of the report mailings. As discussed in Chapter 3, the home energy reports were mailed in the middle of each month, but the monthly electricity usage data is strictly by calendar month. Thus, after July, the monthly electricity usage data may reflect behavior changes resulting from both the first and second mailings, and these mailings could have included different performance designations for the subject household.

In analyzing differences between the different *performance* categories, as opposed to the different *comparison* categories analyzed in the previous sections of this chapter, it is not appropriate to measure the changes in electricity consumption across the different performance categories. This is because there is intended bias built-in to the different performance categories. Homes categorized as “Great” have already demonstrated low energy consumption. Homes categorized as “More than Average” have already demonstrated high energy consumption. To simply compare how the “Great” homes respond to treatment versus how the “More than Average” homes respond to treatment would blur the analysis, because the different performance categories have actually been

categorized based on their electricity usage. This means the low-consuming homes (“Great”) would have a more challenging time finding new ways to conserve energy than would the high-consuming homes (“More than Average”).

Therefore, what is needed is a performance categorization to be assigned to each of the homes in the control group. In this way, the homes categorized as “Great” that received treatment can be compared to the homes categorized as “Great” that did not receive treatment, and similarly for each of the three performance categories. This was done and the results are shown in Table 4.17.

June Performance Category	Experiment Group	Number of Homes	Difference Between June and July (kWh)	Standard Deviation
Great	Treatment	23	471	243
	Control	30	334	145
Good	Treatment	78	402	226
	Control	121	447	224
More than Average	Treatment	80	377	305
	Control	142	456	301

**Table 4.17** Differences in Electricity Consumption by Performance Category

And then calculating the electricity savings, based on an average electricity consumption during June and July of 1,247 kWh, we obtain Table 4.18.

June Performance Category	Electricity Savings (kWh)	Electricity Savings (%)	P-Value
Great	-137	-11.0%	0.0255
Good	45	3.61%	0.1720
More than Average	79	6.34%	0.0661

**Table 4.18** Electricity Savings by Performance Category

The most striking finding in Table 4.18 is that the households who received home energy reports that labeled them as “Great” in terms of their energy efficiency demonstrated an increase in energy consumption of 11%, and this increase is statistically significant with a *P*-value of 0.0255. This 11% increase is in comparison to the households who were also categorized as “Great” in the month of June, but did not receive the home energy reports. Thus, the boomerang effect is observed in this research in spite of the use of injunctive norms in the home energy report. This result indicates that injunctive norms may only function to eliminate the boomerang effect when the boundary condition of financial incentives is present.

## Chapter 5: Normative-Based Billing Analysis

Historically, residents of military family housing have not paid for their utility usage. This has allowed residents to consume energy in their homes without regard for the cost of that energy. However, this is beginning to change. Over the last decade, the Department of Defense has relied on a housing privatization program to modernize its large housing stock (Military Housing Privatization, 2012). Through this program, private companies have paid the huge capital costs associated with new construction and have built thousands of new neighborhoods on military bases throughout the United States. In return, these private companies receive the housing allowance of the military members who reside in the homes on base, with this housing allowance essentially amounting to a rent payment. As part of this transition to housing privatization, the Department of Defense has established regulations that mandate utility billing in an effort to reduce household energy consumption by holding residents financially accountable for their energy consumption. Prior to privatization, homes in military family housing were not individually metered and residents did not receive utility bills. While this transition will take many more years, it is well underway, with one-third of military family housing residents already receiving utility bills (Jowers, 2012).

A couple noteworthy challenges exist in implementing a billing system in military family housing. First, the residents are not accustomed to being held financially accountable for their energy consumption. This makes it especially important that the implemented billing system be perceived as fair. And second, military members that live on base are assigned to live in a particular neighborhood based on their rank. Maintaining fairness in

a billing system is challenging when some neighborhoods contain new, energy-efficient homes and some neighborhoods contain old, inefficient homes. While most military members can choose to live outside the base, some are required to live on the base, depending on their responsibilities. And, of those with a choice, many still choose to live on the base because of the closeness to their work and the familiar community. But once they make a decision to live on the base, they lose some of their autonomy. They are then assigned a home to live in, with the neighborhoods established by rank. Because some neighborhoods are older than others and because of the differences in each floorplan, it could be unfair to charge residents for their gross utility consumption, considering that they do not get to choose their specific home and could end up in an older, less energy-efficient home. Also, in order to “pay the rent” to the private developers, the military directly pays what is called the Basic Allowance for Housing (BAH) to the company each month for each occupied home. This BAH is based on a member’s rank and the geographic region and includes a portion for utilities. The BAH is the amount of money that a military member would receive for housing if they chose to live off of the military installation. Thus, the BAH represents a fair and predictable way to establish the appropriate rent. And because it includes a portion for utilities, this means that the private developer is essentially already receiving utility payments from the residents. So, an important question is how to develop a billing system that holds residents financially accountable when their utility payment is already made for them at a pre-established level.

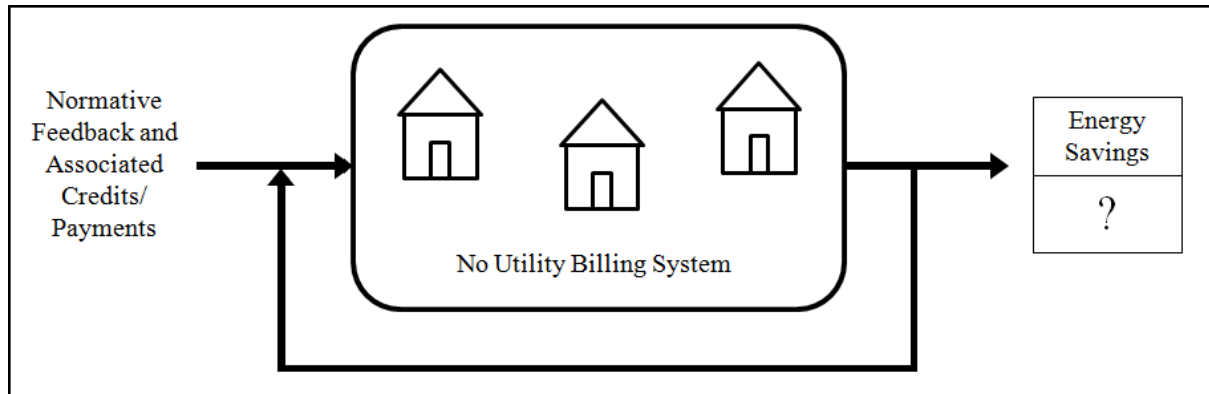


To address these challenges, the mandated billing policies have required that a baseline be established each month for each home type, based on floor plan and age, and that residents make payments for their consumption over the baseline and receive payments for their consumption under the baseline. Such a program introduces financial accountability for energy consumption, and also provides a unique form of feedback to residents different from that provided through a traditional utility billing program.

### 5.1 Purpose of Normative-Based Billing Analysis

Each branch of the military has authority to implement the utility billing program in the way they determine best. This has led to different variations of the baseline billing program. The Air Force, for instance, will implement a program in which the monthly baselines are based on a five year rolling average for that particular month. That is, in any given month, a home will be compared against the average consumption of similar homes in that calendar month over the last five years. The Army, on the other hand, has implemented a billing system of particular interest to the proposed line of research. In their billing system, the monthly baseline is simply the average consumption of similar homes during that actual month. This is essentially the application of normative feedback with rewards or penalties for deviation from the norm. The proposed research will refer to this as a normative-based billing system, and it is illustrated again in Figure 5.1.

Residents are not only provided with feedback each month on how their consumption compares to the consumption of others, but they also have to pay for any deviation above the average and they get rewarded for any deviation below the average.



**Figure 5.1** Variation 3: Normative Feedback as Basis for Utility Billing System

The research need related to these utility billing systems is the development of an optimization model to determine the best possible billing system. Such a model would attempt to maximize the profit of the private company as the owners of the homes. Because their profit is directly impacted by occupancy rates, this approach would indirectly incorporate an element of resident satisfaction that would be impacted by the management of the utility billing program. The profit being maximized would also be impacted by the amount of energy consumed, as ownership is responsible for paying the aggregate utility bill for the community. This results in a certain amount of tension between maintaining occupancy rates, which are not guaranteed, and driving energy conservation behaviors through household utility billing.

The proposed research takes an initial step towards this optimization model by determining the energy savings associated with the implementation of a normative-based billing program by the Army. A normative-based billing system, as already mentioned, is essentially the application of normative feedback with rewards and penalties. Other studies on rewards for energy conservation behavior have consistently found energy

savings (Winett, Kagel, Battalio, & Winkler, 1978) (Slavin, Wodanski, & Blackburn, 1981). Therefore, this study also expects to find positive energy savings. No formal hypothesis was put forward for this third variation of the normative feedback model. As stated in the introduction, the objective of this component of the research was to determine the actual amount of energy savings associated with the introduction of the normative-based billing system. That determination will ultimately feed into an optimization model to analyze the different utility billing programs being considered and implemented by the different branches of the military.

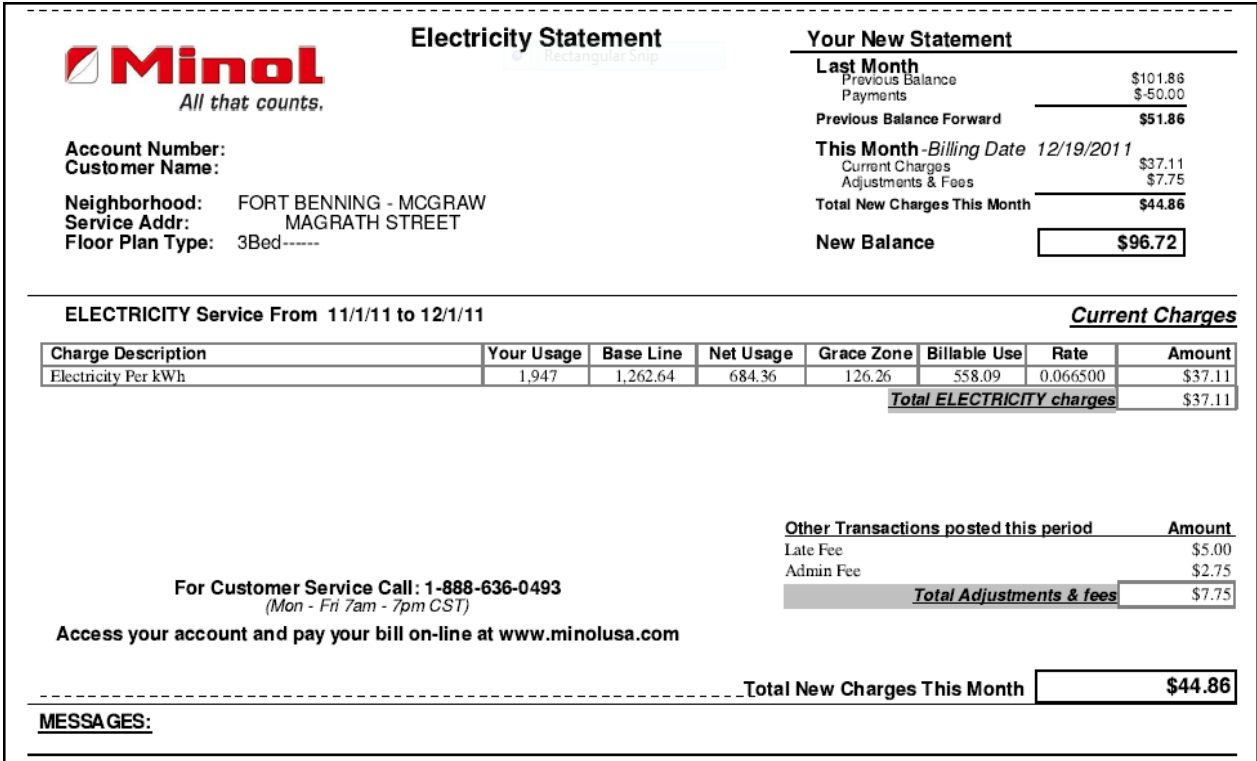
### 5.2 Military Family Housing at Fort Belvoir

The third variation of the normative feedback model was tested through a regression analysis on energy consumption data associated with the implementation of a normative-based billing program at Fort Belvoir in Virginia. The billing program began in June of 2006 with residents in two neighborhoods receiving “mock” utility bills for eight months before “live” billing began in February of 2007. Mock bills were designed to prepare residents for the transition and did not involve any financial transactions. Unfortunately, data are not available for the time period before mock billing began. The available data begin in June of 2006 and continue through December of 2008, representing over 18,000 observations. At different times throughout this period, six additional neighborhoods began receiving mock bills for a few months and then transitioned to live billing. The savings associated with the billing program will be determined by analyzing the impact of the transition from mock billing to live billing, which represents the actual introduction of residents being held financially accountable for their utility usage. The homes on Fort

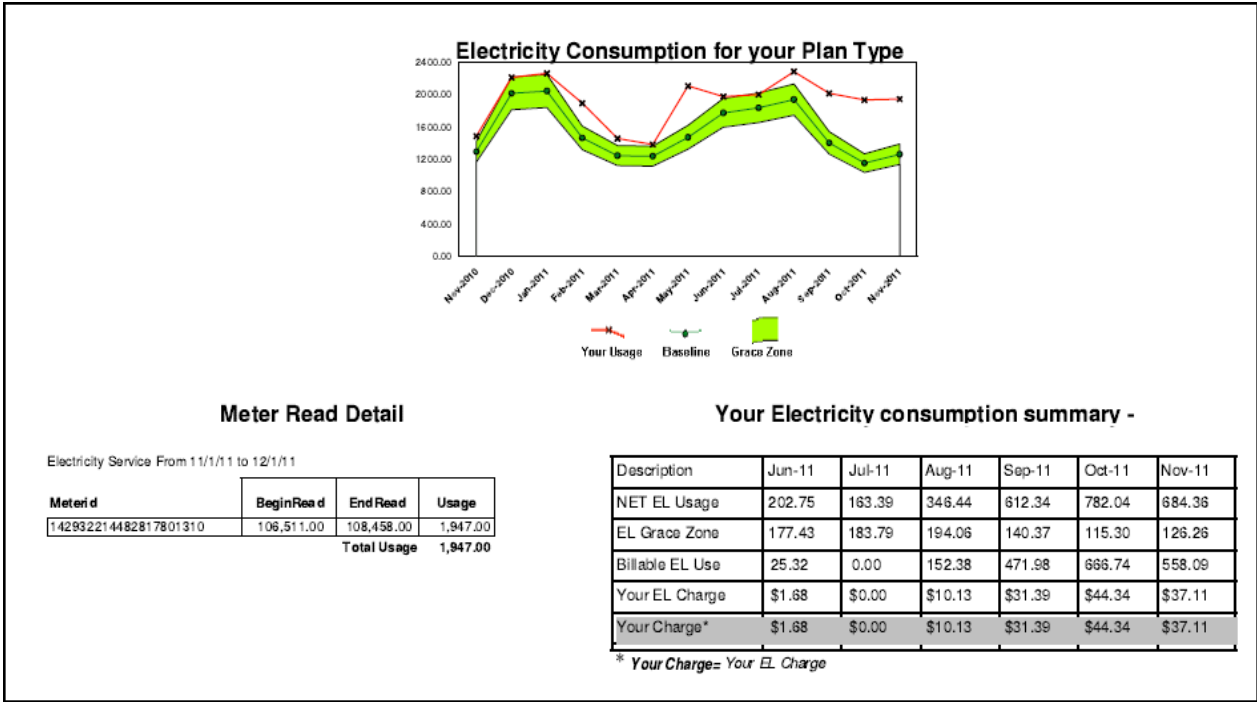
Belvoir are owned by Clark Realty Group and they have provided the data for this analysis.

Fort Belvoir has privatized housing, with 15 neighborhoods containing over 2,000 homes. Around 1,500 of those homes have been built since 2005. Unit types include single family homes, duplexes, and townhouses. The homes are individually metered for utilities, to include water. They are fueled by both electricity and natural gas. The normative-based billing program sends billing statements to the residents each month, holding them financially accountable for both their electricity and natural gas consumption.

The details of the billing program center on the calculation of the baseline consumption each month. This baseline is established for electricity and gas individually, and is calculated as the average consumption of other homes in the same profile. A separate profile exists for each floorplan. After the baseline is calculated, a buffer zone, or “grace zone,” is set at 10% above the baseline and 10% below the baseline. The household’s consumption is compared against the baseline for that month. If it is within the buffer zone, no financial transaction needs to take place. If it is above the buffer zone, the resident is billed for the amount of consumption above the buffer zone. If it is below the buffer zone, the resident receives a credit for the amount of consumption below the buffer zone. Figures 5.2 and 5.3 show excerpts from a sample billing statement. This statement is from a different Army installation and only contains electricity information, but it is still representative of the billing process. For dual fuel billing statements, the billable amounts for each fuel are added together to determine the total charges.



**Figure 5.2** Top Half of Normative-Based Billing Statement



**Figure 5.3** Bottom Half of Normative-Based Billing Statement

While some military privatization projects have only replaced a small portion of a military base’s family housing, the project at Fort Belvoir replaced almost the entire stock of housing. As construction on each new neighborhood completed, the households in that neighborhood would begin receiving mock utility bills. These mock bills looked just like actual bills except that no actual financial transaction would take place. They were intended to prepare the residents for the full transition to live billing. Table 5.1 lists the eight neighborhoods and the month in which each neighborhood transitioned from mock billing to live billing.

<b>Number</b>	<b>Neighborhood</b>	<b>Began Live Billing</b>
1	Herryford Village	Feb-07
2	Vernondale Village	Feb-07
3	Cedar Grove	Sep-07
4	Lewis Village	Oct-07
5	George Washington	Dec-07
6	Rossell Village	Mar-08
7	Colyer Village	Nov-08
8	Fairfax Village	Sep-09

**Table 5.1** Timeline of Transition from Mock Billing to Live Billing

### 5.3 Regression Analysis

The research objective associated with the third variation of the normative feedback model stated: determine overall energy savings associated with the implementation of a normative-based utility billing system into a community previously not held financially accountable for household energy consumption. To accomplish this objective, it is not possible to simply compare energy consumption before live billing started to energy consumption after live billing started. This would not account for variations in weather.

A household's monthly energy consumption is dramatically impacted by that month's weather. The timeline chart on the billing statement in Figure 5.3 demonstrates this. Typically, during summer months, the air conditioner consumes large amounts of electricity. And during winter months, the furnace consumes large amounts of either electricity or natural gas, and hot water heaters have to work harder as well. Certain months in the spring and summer can allow for lower energy consumption due to moderate weather. These dynamics, of course, vary from location to location.

A multiple regression analysis, however, can account for the changes in weather over time. With household energy consumption as a continuous dependent variable, two independent variables related to the weather were considered in the analysis: heating degree days (HDD) and cooling degree days (CDD). These continuous variables provide quantification for the amount of heating and cooling required in any given month. By controlling for the differences between weather before the billing transition and weather after the billing transition, an analysis could effectively be made on the impact of live billing. The regression analysis included other independent variables as well, some of which were continuous, and some of which were categorical.

### 5.3.1 Description of Data

The data available for this analysis begin in June of 2006. That is the month that the Herryford and Vernondale villages began receiving mock utility bills. The data extend through December of 2008, with the exception of April of 2008, which is missing for unknown reasons. The raw data received listed each home and their respective gas and electric consumption each month. These values were converted into a single value of

energy consumption by converting each to kBtu and adding them together. The data also included square footage of each home, the neighborhood, and the unit type. Unoccupied homes and faulty meter readings were deleted. The resulting data set included over 18,000 observations. Additional fields were included in the data set. Specifically, a value of zero was assigned to an observation made during a month in which mock bills were received, while a value of one was assigned to an observation made during a month in which live bills were received. This represents our variable of interest. Also, weather data was incorporated in the form of heating degree days (HDD) and cooling degree days (CDD) for each month.

An initial exploration of the data reveals some helpful descriptions. For instance, about a quarter of the observations took place during mock billing months, as shown below in

Table 5.2.

	<b>Frequency</b>	<b>Percent</b>	<b>Cumulative</b>
Mock Billing	4,377	24.03	24.03
Live Billing	13,839	75.97	100
Total	18,216	100	

**Table 5.2** Breakdown of Mock Billing Versus Live Billing Frequency

Also, since the goal is to measure the energy savings resulting from the implementation of the billing system, we can take a quick look at the energy consumed under mock billing versus live billing, as shown in Table 5.3.



<b>Summary of Total kBtu</b>			
	<b>Mean</b>	<b>Standard Deviation</b>	<b>Frequency</b>
Mock Billing	7779	3484	4377
Live Billing	7726	3345	13839
Total	7739	3379	18216

**Table 5.3** Energy Consumption During Mock Billing Versus Live Billing

At first glance, this would indicate a fairly negligible energy savings of 0.68%. But this would be an incomplete analysis, due especially to the monthly variations in weather. To account for such variations, as well as other influencing variables, such as the square footage of the house and the house type (townhouse, duplex, or single family home), a multiple regression analysis is required. The total monthly energy consumed by each household is the continuous dependent variable, called Total kBtu, and the list of independent variables is as follows:

- Square Footage
- Heating Degree Days (HDD)
- Cooling Degree Days (CDD)
- Live Billing (0 for mock billing; 1 for live billing)
- Unit Type (1=Townhouse, 2=Duplex, 3=Single Family Home)
- Village Number (1-8, as defined in Table 5.1)

Each of these variables accounts for either the variety between the physical characteristics of the houses, the variety between the neighborhoods to include differing rank structure, or the variety in monthly weather conditions. The variable of interest is “Live Billing” whose coefficient will give us direct information on the savings associated

with the transition from mock billing to live billing across all the neighborhoods.

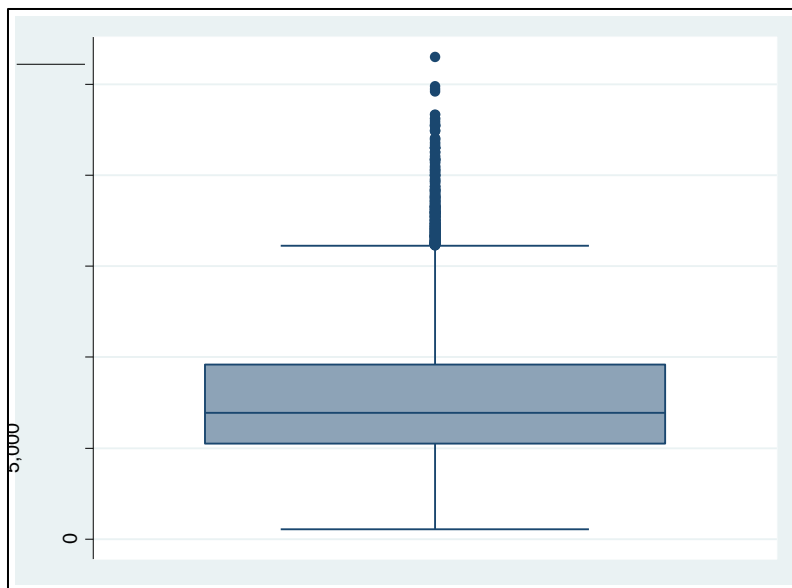
Unfortunately, no data is available for the number of occupants in each home.

### 5.3.2 Dependent Variable

Before jumping into the regression analysis, we should take a look at each variable. First, let's look at Table 5.4 for some descriptive statistics and Figure 5.4 for a boxplot of our dependent variable, Total kBtu.

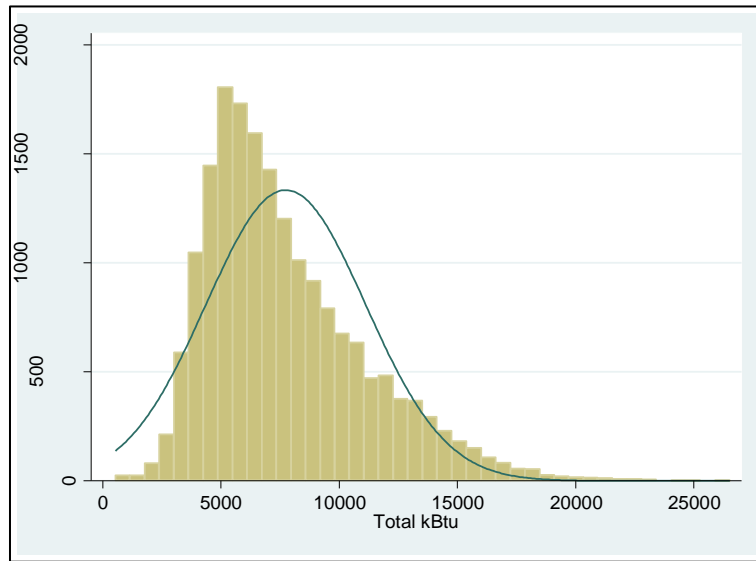
Variable	Observations	Mean	Standard Deviation	Min	Max
Total kBtu	18216	7739	3379	530	26519

**Table 5.4** Descriptive Statistics for Total kBtu



**Figure 5.4** Boxplot of Total kBtu

We can see that Total kBtu has a mean of 7,739 kBtu and is skewed to the right. We can also examine its distribution in Figure 5.5 and note that it has a fairly normal distribution, though certainly not perfectly normal.



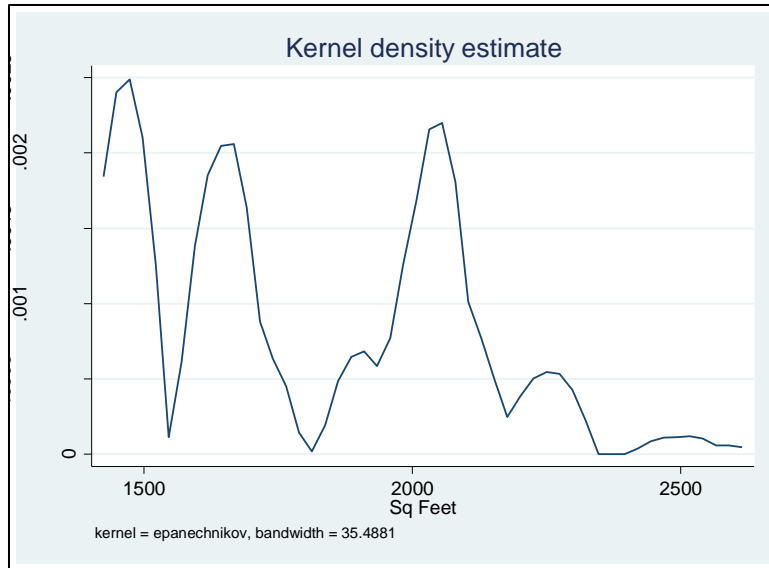
**Figure 5.5** Distribution of Total kBtu

### 5.3.3 Independent Variables

The first independent variable to be examined is Square Footage. Table 5.5 presents the descriptive statistics and Figure 5.6 shows the distribution. This is a continuous variable in theory, but because of the limited number of floorplans, it plots as more of a categorical variable.

<b>Variable</b>	<b>Observations</b>	<b>Mean</b>	<b>Standard Deviation</b>	<b>Min</b>	<b>Max</b>
Square Footage	18216	1794	280	1460	2579

**Table 5.5** Descriptive Statistics for Square Footage



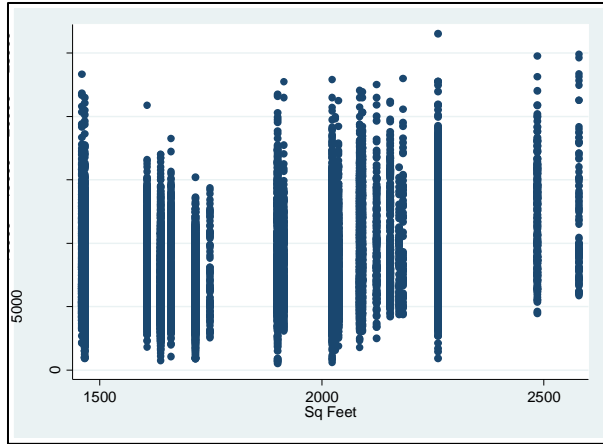
**Figure 5.6** Distribution of Square Footage

Nevertheless, we will treat this as a continuous variable in our analysis. HDD and CDD behave in a similar manner because of the limited number of months involved in the analysis. They also will be treated as continuous variables and have the following descriptive statistics:

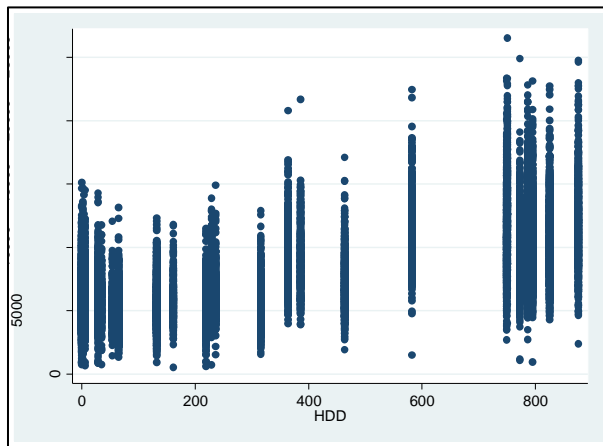
Variable	Observations	Mean	Standard Deviation	Min	Max
HDD	18216	335	336	0	876
CDD	18216	104	128	0	368

**Table 5.6** Descriptive Statistics for HDD and CDD

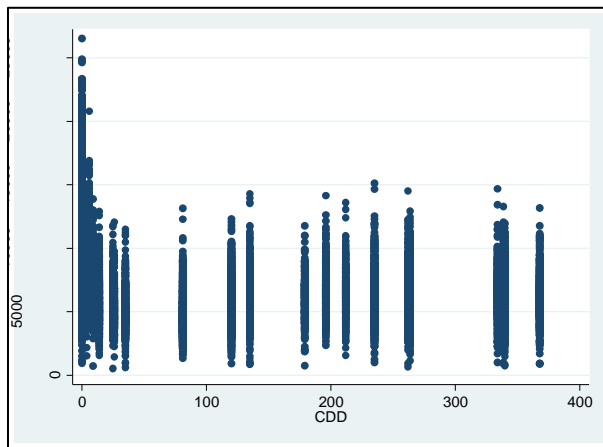
We need to check whether a linear relationship exists between each of these three continuous independent variables and our dependent variable. The scatter plots for these variables are shown in Figures 5.7 to 5.9. We can see that the relationships are fairly linear, and that Total kBtu generally increases as each independent variable increases. The exception is CDD, which maintains a slope near zero, due in part to the decrease in natural gas required for hot water heating during the summer when CDD is highest.



**Figure 5.7** Scatter Plot of Square Footage Versus Total kBTu



**Figure 5.8** Scatter Plot of HDD Versus Total kBTu



**Figure 5.9** Scatter Plot of CDD Versus Total kBTu

For the categorical variables of Unit Type and Village, we observe the following characteristics in Tables 5.7 and 5.8.

House Type	Frequency	Percent	Cumulative
Townhouse	2,876	15.79	15.79
Duplex	8,897	48.84	64.63
SFH	6,443	35.37	100
Total	18,216	100	

**Table 5.7** Breakdown of Homes by Unit Type

Village Number	Village	Frequency	Percent	Cumulative
1	Herryford Village	4,429	24.31	24.31
2	Vernondale Village	4,569	25.08	49.4
3	Cedar Grove	1,192	6.54	55.94
4	Lewis Village	4,509	24.75	80.69
5	George Washington	2,483	13.63	94.32
6	Rossell Village	734	4.03	98.35
7	Colyer Village	217	1.19	99.54
8	Fairfax Village	83	0.46	100
	Total	18,216	100	

**Table 5.8** Breakdown of Homes by Neighborhood

Of most notable interest from these tables is the fact that about 75% of the observations came from just three neighborhoods.

In addition to controlling for the above continuous and categorical variables, we also need to account for the dependency associated with the repetitive observations made on the same family again and again each month. This can be accomplished by clustering on a variable that uniquely identifies each family. This variable, called Family ID, assigns a

unique number not just to each house, but to each family. Thus, each time a family moved out of a house during the study time period, the new family that moved in was assigned a new Family ID. This is especially important in military family housing where residents move every three years on average. We find that there are 1,622 unique families that lived in the 1,095 homes during the course of the time period under investigation.

5.4 Regression Results and Interpretation

Running the regression analysis yields the results shown in Table 5.9. The full software output is found in Appendix D.

<b>Independent Variable</b>	<b>Regression Coefficient</b>
Square Feet	3.65 (0.000)
HDD	9.08 (0.000)
CDD	7.37 (0.000)
Live Billing	-1091.14 (0.000)
House Type	
Townhouse	-----
Duplex	816.18 (0.000)
SFH	1882.20 (0.000)
Village	
Herryford Village	-----
Vernondale Village	-410.56 (0.002)
Cedar Grove	-1991.04 (0.000)
Lewis Village	-1544.14 (0.000)
George Washington	-1161.20 (0.000)
Rossell Village	-1550.95 (0.000)
Colyer Village	-1964.74 (0.000)
Fairfax Village	-2444.81 (0.000)
Constant	-1987.62 (0.000)

Note:  $r^2 = 0.627$ ;  $P$ -values in parentheses

**Table 5.9** Regression Results for Billing Analysis

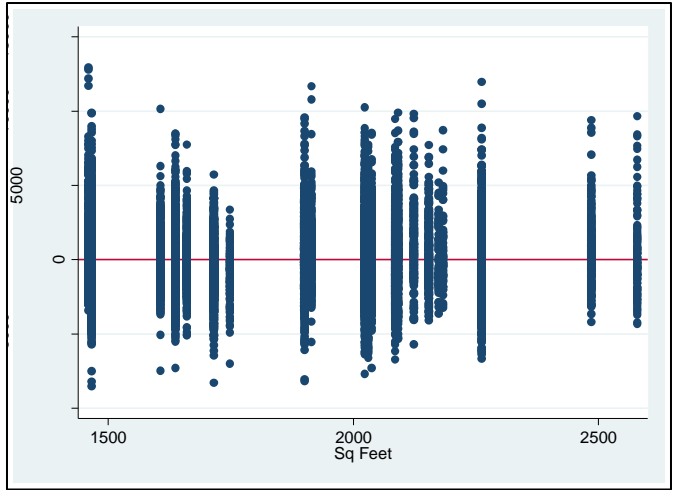
Each variable is highly significant and our r-squared indicates that our variables are accounting for a sizable amount of the variation in the observations. Our coefficient of interest, Live Billing, tells us that the transition from mock billing to live billing yielded 1,091 kBtu in monthly energy savings. *With mean monthly energy consumption of 7,739 kBtu, this represents 14.1% savings.* But we can make some other interesting observations from this output as well. We can see that for every 1,000 square foot increase, we find an increase of 3,650 kBtu. We see that heating consumes more energy than cooling. We notice that, while controlling for house size through the square footage variable, we still see that single family homes consume more energy than duplexes which consume more than townhomes. To investigate the neighborhood influences in more details, Table 5.10 provides a breakdown by rank.

<b>Number</b>	<b>Village Name</b>	<b>Rank</b>
1	Herryford Village	E1-E5
2	Vernondale Village	E6-E8
3	Cedar Grove	O4/O5
4	Lewis Village	E1-E9
5	George Washington	E1-E8
6	Rossell Village	O1/O5
7	Colyer Village	E6-E8
8	Fairfax Village	O4/O5

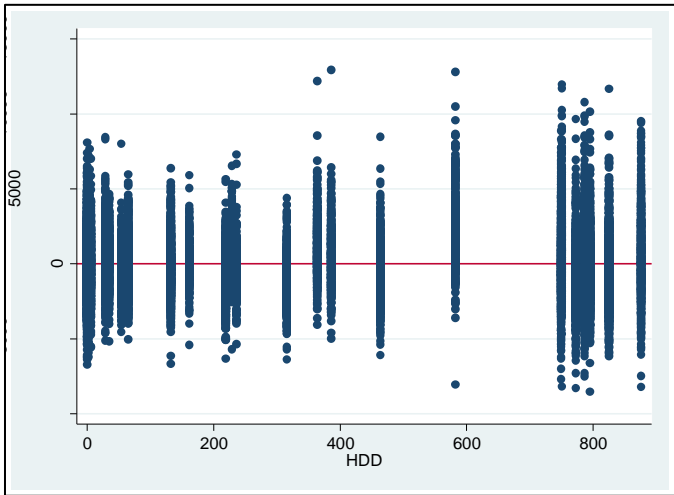
**Table 5.10** Breakdown of Neighborhoods by Rank

We also need to take a look at the residual plots to ensure they are centered about zero. They are, for the most part, which confirms their homoskedasticity. Figure 5.10 to 5.12 show the residual plots for the continuous independent variables.

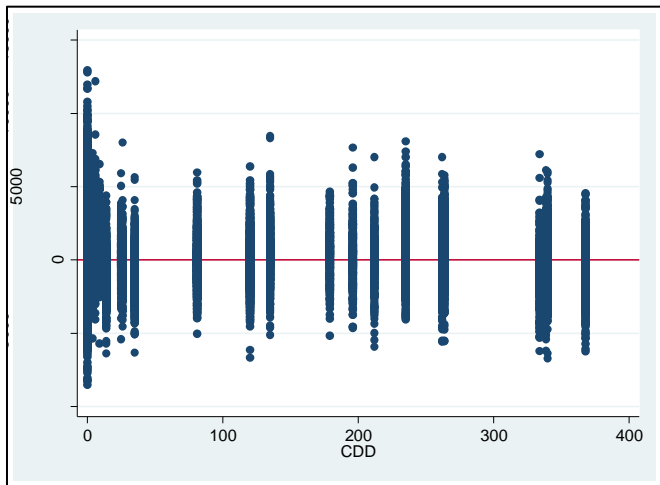




**Figure 5.10** Residual Plot for Square Footage



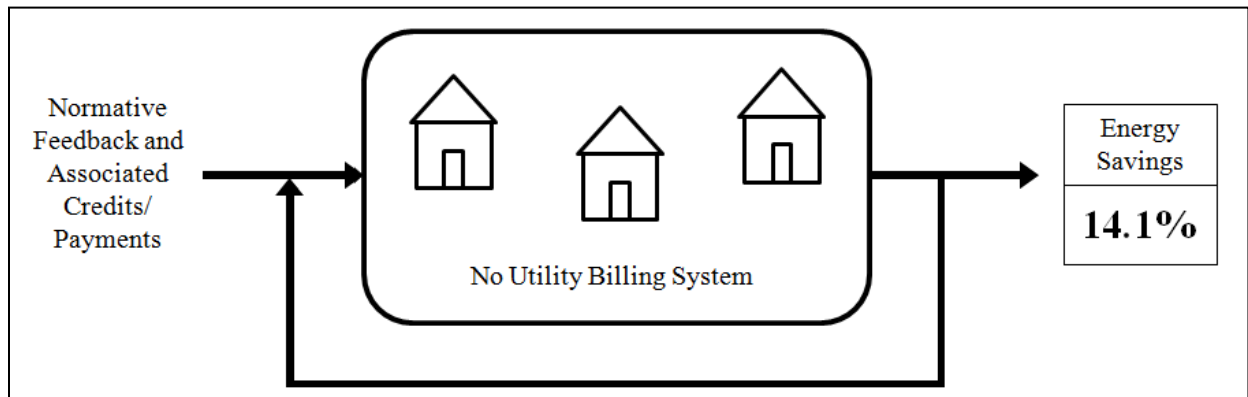
**Figure 5.11** Residual Plot for HDD



**Figure 5.12** Residual Plot for CDD

A final note about the regression results regards the assumption of normal distribution we made for the dependent variable, Total kBtu. The assumption was reasonable, but if we were to take the natural logarithm of Total kBtu, we would actually find a more normal distribution. When the regression analysis was run for the transformed variable, the coefficient for Live Billing was  $-.1387$ , indicating a savings of approximately 13.9%. This is comparable to the 14.1% savings we identified without transforming the dependent variable.

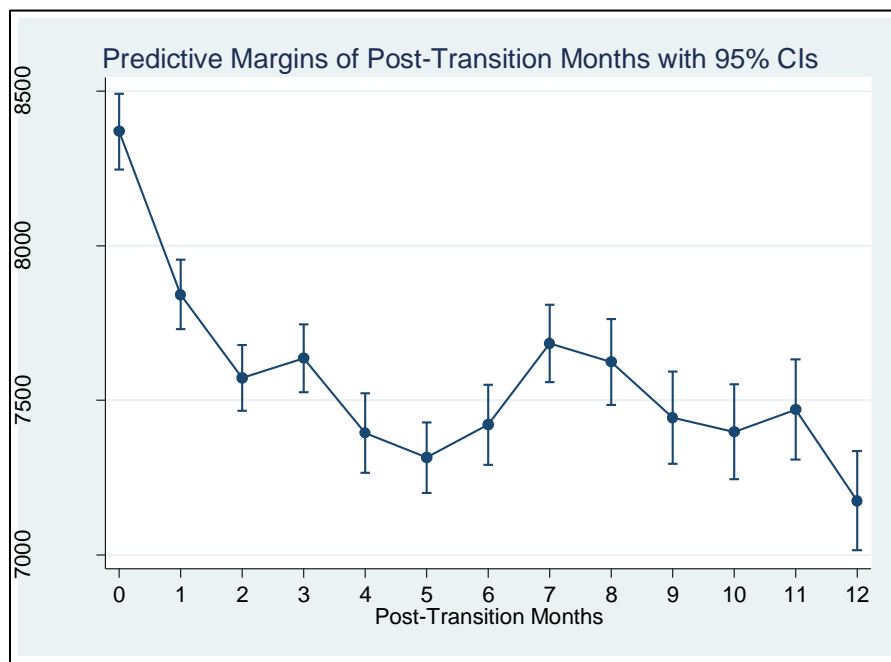
The primary conclusion from this study is the identification of 14.1% savings in energy consumption as a result of holding residents financially accountable for their utility usage. This conclusion is displayed in Figure 5.13.



**Figure 5.13** Energy Savings of Normative-Based Billing Implementation

As the ultimate purpose for identifying these energy savings is to produce an optimization model allowing comparison of different billing programs, it is also useful to examine the impact of the billing system over time. This will provide insight on whether residents maintain their initial response to the billing implementation or whether it changes over time. This would be a relevant observation to incorporate into the future

optimization. To perform this analysis, we first need to generate a new variable called Post-Transition Months. This simply measures the amount of time that a particular family has lived in the home since the transition to live billing. By inserting this variable into our regression analysis, we can then examine the predictive margins of this variable. The chart in Figure 5.14 shows the predicted values of Total kBtu, based on the regression equation, plotted against the new variable of Post-Transition Months.



**Figure 5.14** Predictive Margins of Post-Transition Months

This graph indicates that residents adjusted their energy consuming behaviors most significantly in the first two months of live billing. After this initial drop-off, their behaviors slightly rebounded between months five through seven, before tapering again.

## Chapter 6: Conclusions and Recommendations

### 6.1 Summary of Research Results

This research has studied one of the more promising innovations in the field of energy conservation. Over the last several years, a company called OPOWER has incorporated research from the field of social norms into home energy reports which they have mailed to hundreds of thousands of households. These reports provide normative feedback, meaning they compare the household's energy consumption with that of other homes in the area. The resulting energy savings from the reports have ranged between 1.4% and 3.1%. This extensive application of social norms to influence energy conservation behaviors has been described by this research as the basic normative feedback model.

This research has tested three variations of that basic normative feedback model, measuring the associated energy savings of each variation. The first two variations were tested through an experiment that involved mailing home energy reports to residents of military family housing on Joint Base Andrews in Maryland. The third variation involved analyzing the transition to a normative-based utility billing system in military family housing on Fort Belvoir in Virginia.

The home energy report experiment was conducted at Joint Base Andrews, a base in which no utility billing program is currently in place. The experiment tested: 1) whether normative feedback could generate energy savings in the absence of a utility billing system that would provide financial incentive for conservation, and 2) whether increasing the proximity of the comparisons from the neighborhood level, to the street level, and to the next-door neighbor level could generate increasing levels of energy savings. The

experimental analysis revealed an overall electricity savings of 3.8%, indicating that normative feedback can still generate energy savings even without financial incentives. The experiment also found that increasing the proximity of the comparison level from neighborhood to street increased the electricity savings from 3.8% to 4.9%, but then further increasing the comparison level to next-door neighbor actually decreased the electricity savings down to 2.8%. This indicates the effectiveness of increasing the proximity of comparison, but also indicates that increasing the proximity level too far actually reduces the effectiveness of the normative feedback.

In addition to the home energy report experiment, this research also examined the use of normative feedback as the basis for a utility billing system. With the military transitioning to residential utility billing, Fort Belvoir implemented a billing system in which household energy consumption is compared to the average consumption, and the residents either get billed for over-consumption or receive a payment for under-consumption. This research performed a regression analysis to determine the energy savings that resulted from the implementation of this normative-based billing system and found the savings to be 14.1%.

### 6.2 Contributions and Implications of the Research

As normative feedback for energy consumption has emerged as a highly cost-effective and scalable means of obtaining energy savings, it has received increasing research attention. Other research projects have studied how variables such as the frequency of the feedback, the mode of the feedback, and the format of the feedback can impact the

resulting energy savings. But there remain some significant gaps in the body of knowledge, and this research helps close three of those gaps.

First, this research tested one of the boundary conditions of the basic normative feedback model. Whereas all of OPOWER's home energy reports are provided to residences that receive regular utility bills, this research demonstrated that significant energy savings can still be achieved without financial incentives involved. This indicates that although financial incentives may still influence behaviors, the normative feedback model does not require their presence in order to generate energy savings. Thus, future applications of normative feedback for energy conservation should also target facilities in which the occupants do not pay for utility consumption. This could include providing normative feedback to residents of college dormitories, apartment complexes, and even office buildings.

Second, this research tested whether increasing the proximity level of the comparisons in the home energy reports can increase the resulting energy savings. We found that increasing the proximity of the comparison from "Neighborhood" to "Street" indeed increased energy savings, but that further increasing the proximity to "Next-Door Neighbor" decreased energy savings to the lowest savings percentage of all three comparison levels. This idea of comparison proximity increasing the impact of normative feedback has been suggested and tested in one other study within the context of hotel towel reuse, but this is the first study to establish three different comparison levels and to conduct an experiment in the realm of household energy conservation. The implication of this portion of the research is that there exists a "sweet spot" in setting the

proximity of comparisons in normative feedback. Future applications of normative feedback for household energy conservation can increase the treatment effect by increasing the proximity of the comparisons to the “Street” level.

Third, this research measures the energy savings that resulted from the implementation of a normative-based utility billing system. The measured savings of 14.1% provide an indication on the impact of financial incentives above and beyond the normative feedback, when the amount of those financial incentives are determined based on deviation from normative behavior. No previous research has investigated the implementation of a billing system that is based on normative feedback and normative behaviors. This research measured the energy savings and determined how those savings were obtained over time, taking the first steps the development of a billing optimization model for potential use by the Department of Defense in establishing utility billing programs.

The concept of presenting information on socially normative behavior as a tool to influence behaviors is of particular interest to the project manager. A project manager has to find ways to motivate project team members and normative feedback should be one of the tools considered. For instance, a construction project manager might encourage positive safety behaviors on the job site by providing normative feedback to employees regarding safety metrics on other jobs. This research would indicate that the normative feedback provided ought to provide comparisons at a certain optimum proximity level. In the case of safety comparisons, it may be optimal to provide comparisons to other construction jobs within the same city, as opposed to a higher

proximity level such as nationwide metrics or a lower proximity level such as local company metrics.

### 6.3 Limitations of the Research

Two aspects of the home energy report experiment cause there to be limitations in the extensibility of the results. The home energy report experiment was conducted exclusively in the summer, and only electricity usage data was available. Thus, while the conclusions of this research would likely apply to winter months and natural gas consumption, that cannot be confirmed by this research. An experiment conducted over the course of an entire year would improve the reliability of the results.

Also, all of the houses involved in this research, both for the home energy report experiment and the normative-based billing, exist on military installations with military families living in them. There are unique aspects of the military and military family housing that could have produced unique results. For instance, the neighborhoods are all established based on the rank of the military member in the household. This leads to very homogenous neighborhoods, both in terms of the professional demographics, but also the physical houses themselves, as home size is strongly impacted by rank as well. This homogeneity could lead to responses to normative feedback that differ from the population at large. It may be, perhaps, that social norms govern behavior to a greater degree in the military environment, an environment in which standardization and conformity are often desirable characteristics.



#### 6.4 Further Research

As the military continues to transition to utility billing in family housing, some details of the program remain unsettled. The Army is far ahead of the other services in terms of the rate of transition. The other services are observing the Army's outcomes as they craft their own programs. The need exists for developing an optimization model to determine a billing program that satisfies the requirements of the government to reduce energy consumption, while optimizing resident satisfaction and contractor profit. This research evaluates key aspects of the Army's implementation of normative-based billing at Fort Belvoir, and thereby takes an initial step towards developing such an optimization model, but much more work needs to be done on this. Determining energy savings and investigating occupant response over time are only the first steps.

Future work could also focus on further improvements to the normative feedback model. While this research identified the "Street" level of comparison as the optimum level out of the three proximity levels tested, there may exist a proximity level that could further increase effectiveness without beginning to suffer from the effects of the actor-observer bias. For instance, a comparison to the nearest 10 homes may be the true "sweet spot." Future home energy report experiments should consider testing a higher number of proximity levels, if the number of observations could be high enough to support this from a statistical perspective.

## Appendix A: Cover Letter for Home Energy Reports



July 13, 2012

Dear Resident,

The University of Maryland and Liberty Park at Andrews have partnered to provide you the enclosed Home Energy Report. The purpose of this report is to provide you with feedback on your household's electricity usage as it compares to others in the community. Please note that **this is not a bill**. You have been randomly selected to receive this report as part of a research study by the University of Maryland, and can expect to receive this report for three consecutive months. If you have any questions or desire further information, please contact Maj Robert Young at 719-314-7328 or [robyoung@umd.edu](mailto:robyoung@umd.edu). Thank you!

Sincerely,

A handwritten signature in black ink that reads "Robert M. Young". The signature is written in a cursive style.

Robert M. Young, Maj, USAF  
AFIT/CIP Student  
PhD Candidate, University of Maryland

---

**LIBERTY PARK AT ANDREWS**  
2097 SAN ANTONIO BLVD. ANDREWS AFB, MD 20762  
PHONE: 301-736-8082 FAX: 301-736-8085  
[WWW.ANDREWSFAMILYHOUSING.COM](http://WWW.ANDREWSFAMILYHOUSING.COM)

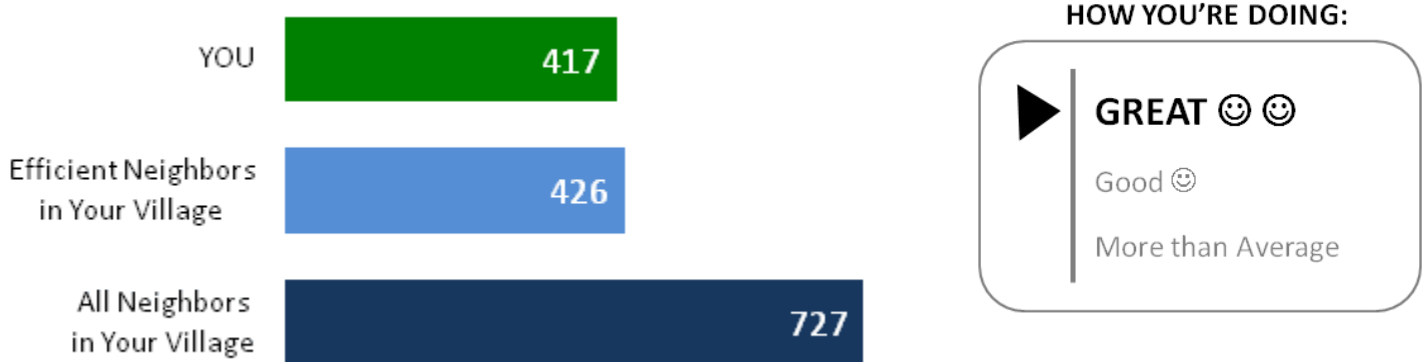
## Appendix B: Home Energy Reports

# Home Energy Report

for

4028 Ashwood Circle Unit 2

**June 2012 Household Comparison** | You used **2% LESS** electricity than your most efficient neighbors.



Note: The above numbers are normalized for home size and represent monthly electricity usage per square foot (watt-hr/ft<sup>2</sup>).

## WHO ARE YOUR "NEIGHBORS"?

**"All Neighbors":** All the homes in your village that were occupied for all of last month.

**"Efficient Neighbors":** The most efficient 20% of all the homes in your village that were occupied for all of last month.

## TIPS TO SAVE ENERGY IN JULY

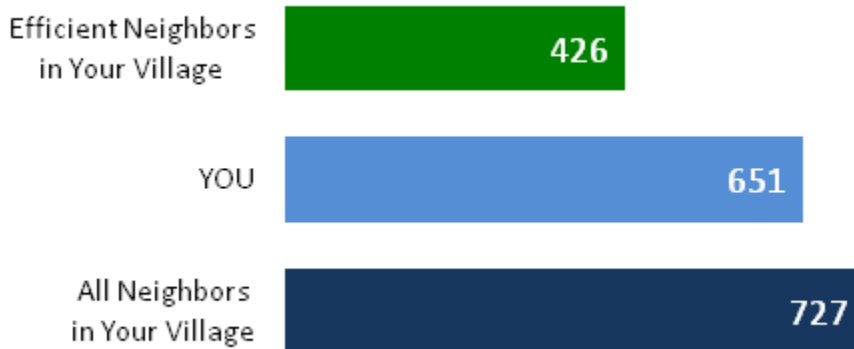
- Check to see that windows and doors are closed when cooling your home.
- Raise the temperature setting on your thermostat when your home is unoccupied.
- Turn things off when you are not in the room such as lights, TVs, entertainment systems, and computers.
- Plug home electronics, such as TVs and DVD players, into power strips; turn the power strips off when the equipment is not in use—TVs and DVDs in standby mode still use several watts of power.

# Home Energy Report

for

4021 Ashwood Circle Unit 1

**June 2012 Household Comparison** | You used **53% MORE** electricity than your most efficient neighbors.



## HOW YOU'RE DOING:



Note: The above numbers are normalized for home size and represent monthly electricity usage per square foot (watt-hr/ft<sup>2</sup>).

### WHO ARE YOUR "NEIGHBORS"?

**"All Neighbors"**: All the homes in your village that were occupied for all of last month.

**"Efficient Neighbors"**: The most efficient 20% of all the homes in your village that were occupied for all of last month.

### TIPS TO SAVE ENERGY IN JULY

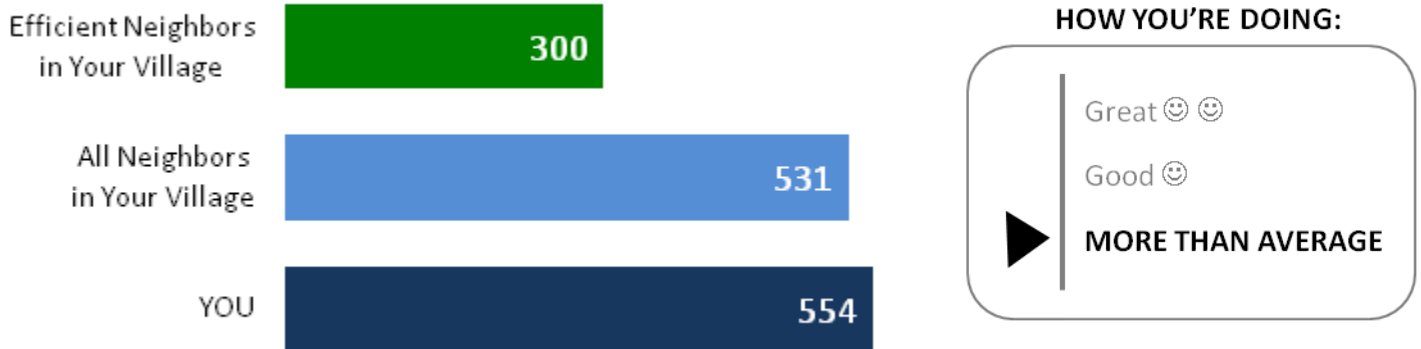
- Check to see that windows and doors are closed when cooling your home.
- Raise the temperature setting on your thermostat when your home is unoccupied.
- Turn things off when you are not in the room such as lights, TVs, entertainment systems, and computers.
- Plug home electronics, such as TVs and DVD players, into power strips; turn the power strips off when the equipment is not in use—TVs and DVDs in standby mode still use several watts of power.

# Home Energy Report

for

2024B Bedford Square

**June 2012 Household Comparison** | You used **4% MORE** electricity than neighbors in your village.



Note: The above numbers are normalized for home size and represent monthly electricity usage per square foot (watt-hr/ft<sup>2</sup>).

## WHO ARE YOUR "NEIGHBORS"?

**"All Neighbors":** All the homes in your village that were occupied for all of last month.

**"Efficient Neighbors":** The most efficient 20% of all the homes in your village that were occupied for all of last month.

## TIPS TO SAVE ENERGY IN JULY

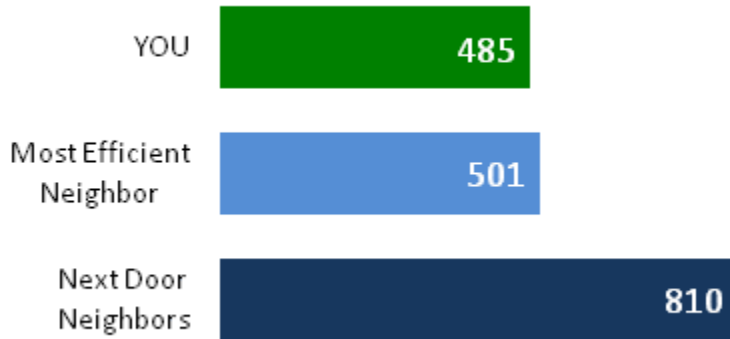
- Check to see that windows and doors are closed when cooling your home.
- Raise the temperature setting on your thermostat when your home is unoccupied.
- Turn things off when you are not in the room such as lights, TVs, entertainment systems, and computers.
- Plug home electronics, such as TVs and DVD players, into power strips; turn the power strips off when the equipment is not in use—TVs and DVDs in standby mode still use several watts of power.

# Home Energy Report

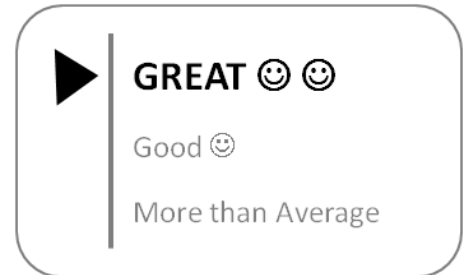
for

2039 Bedford Drive

**June 2012 Household Comparison** | You used **3% LESS** electricity than your most efficient neighbor.



## HOW YOU'RE DOING:



Note: The above numbers are normalized for home size and represent monthly electricity usage per square foot (watt-hr/ft<sup>2</sup>).

## WHO ARE YOUR "NEIGHBORS"?

**"Next Door Neighbors"**: Four neighboring homes, specifically the nearest two occupied homes on each side of your home.

**"Most Efficient Neighbor"**: The most efficient of the four neighboring homes.

## TIPS TO SAVE ENERGY IN JULY

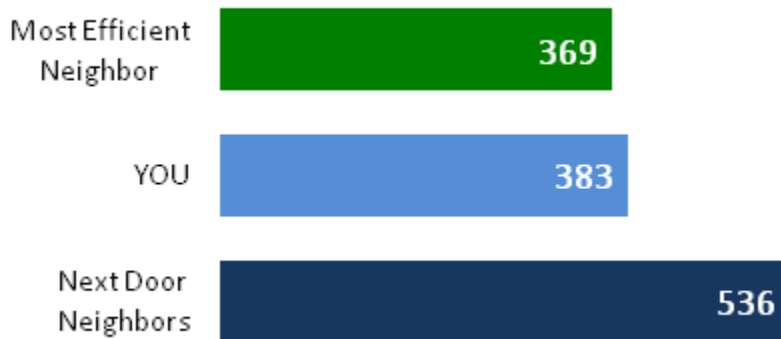
- Check to see that windows and doors are closed when cooling your home.
- Raise the temperature setting on your thermostat when your home is unoccupied.
- Turn things off when you are not in the room such as lights, TVs, entertainment systems, and computers.
- Plug home electronics, such as TVs and DVD players, into power strips; turn the power strips off when the equipment is not in use—TVs and DVDs in standby mode still use several watts of power.

# Home Energy Report

for

2 Airey Court

**June 2012 Household Comparison** | You used **4% MORE** electricity than your most efficient neighbor.



## HOW YOU'RE DOING:



Note: The above numbers are normalized for home size and represent monthly electricity usage per square foot (watt-hr/ft<sup>2</sup>).

## WHO ARE YOUR "NEIGHBORS"?

**"Next Door Neighbors"**: Four neighboring homes, specifically the nearest two occupied homes on each side of your home.

**"Most Efficient Neighbor"**: The most efficient of the four neighboring homes.

## TIPS TO SAVE ENERGY IN JULY

- Check to see that windows and doors are closed when cooling your home.
- Raise the temperature setting on your thermostat when your home is unoccupied.
- Turn things off when you are not in the room such as lights, TVs, entertainment systems, and computers.
- Plug home electronics, such as TVs and DVD players, into power strips; turn the power strips off when the equipment is not in use—TVs and DVDs in standby mode still use several watts of power.

For additional information, or if you have any questions, please contact Maj Robert Young at 719-314-7328 or [robyoung@umd.edu](mailto:robyoung@umd.edu).

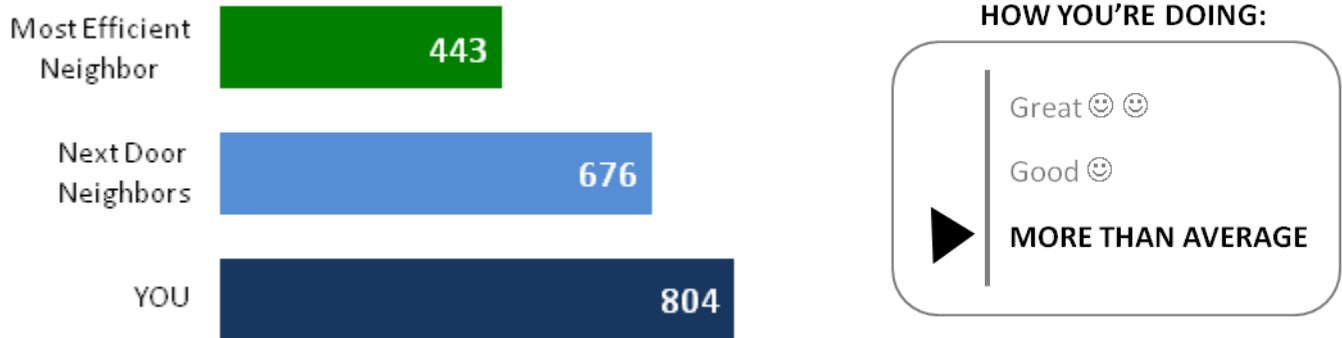


# Home Energy Report

for

4023 Ashwood Circle Unit 1

**June 2012 Household Comparison** | You used **19% MORE** electricity than your next door neighbors.



Note: The above numbers are normalized for home size and represent monthly electricity usage per square foot (watt-hr/ft<sup>2</sup>).

## WHO ARE YOUR "NEIGHBORS"?

**"Next Door Neighbors":** Four neighboring homes, specifically the nearest two occupied homes on each side of your home.

**"Most Efficient Neighbor":** The most efficient of the four neighboring homes.

## TIPS TO SAVE ENERGY IN JULY

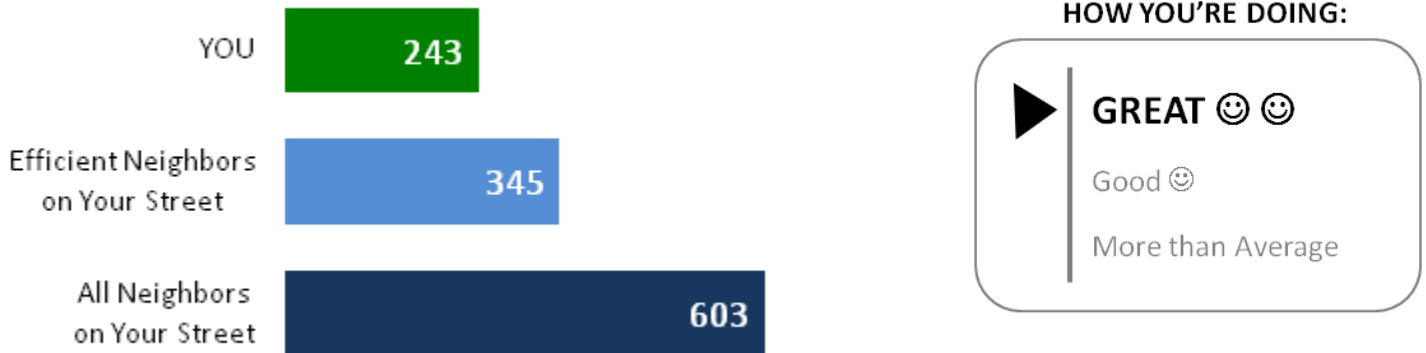
- Check to see that windows and doors are closed when cooling your home.
- Raise the temperature setting on your thermostat when your home is unoccupied.
- Turn things off when you are not in the room such as lights, TVs, entertainment systems, and computers.
- Plug home electronics, such as TVs and DVD players, into power strips; turn the power strips off when the equipment is not in use—TVs and DVDs in standby mode still use several watts of power.

# Home Energy Report

for

2048A Bedford Drive

**June 2012 Household Comparison** | You used **30% LESS** electricity than your most efficient neighbors.



Note: The above numbers are normalized for home size and represent monthly electricity usage per square foot (watt-hr/ft<sup>2</sup>).

## WHO ARE YOUR "NEIGHBORS"?

**"All Neighbors":** All the homes on your street that were occupied for all of last month.

**"Efficient Neighbors":** The most efficient 20% of all the homes on your street that were occupied for all of last month.

## TIPS TO SAVE ENERGY IN JULY

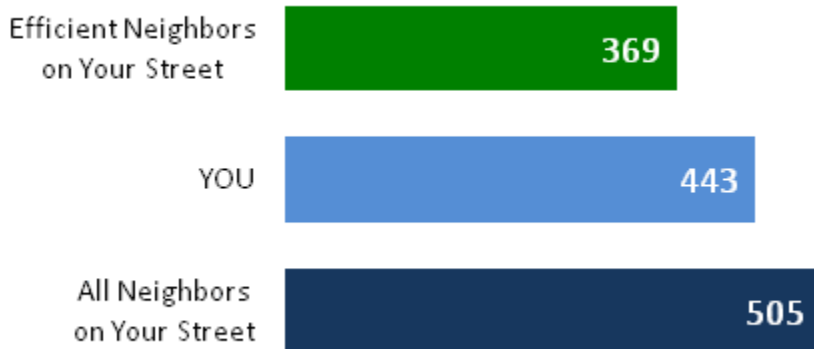
- Check to see that windows and doors are closed when cooling your home.
- Raise the temperature setting on your thermostat when your home is unoccupied.
- Turn things off when you are not in the room such as lights, TVs, entertainment systems, and computers.
- Plug home electronics, such as TVs and DVD players, into power strips; turn the power strips off when the equipment is not in use—TVs and DVDs in standby mode still use several watts of power.

# Home Energy Report

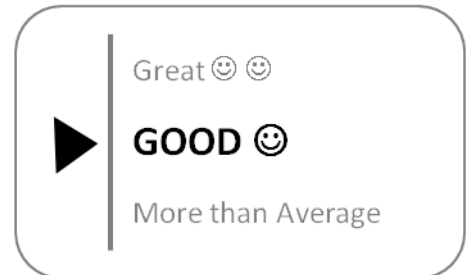
for

4023 Ashwood Circle Unit 3

**June 2012 Household Comparison** | You used **20% MORE** electricity than your most efficient neighbors.



## HOW YOU'RE DOING:



Note: The above numbers are normalized for home size and represent monthly electricity usage per square foot (watt-hr/ft<sup>2</sup>).

## WHO ARE YOUR "NEIGHBORS"?

**"All Neighbors"**: All the homes on your street that were occupied for all of last month.

**"Efficient Neighbors"**: The most efficient 20% of all the homes on your street that were occupied for all of last month.

## TIPS TO SAVE ENERGY IN JULY

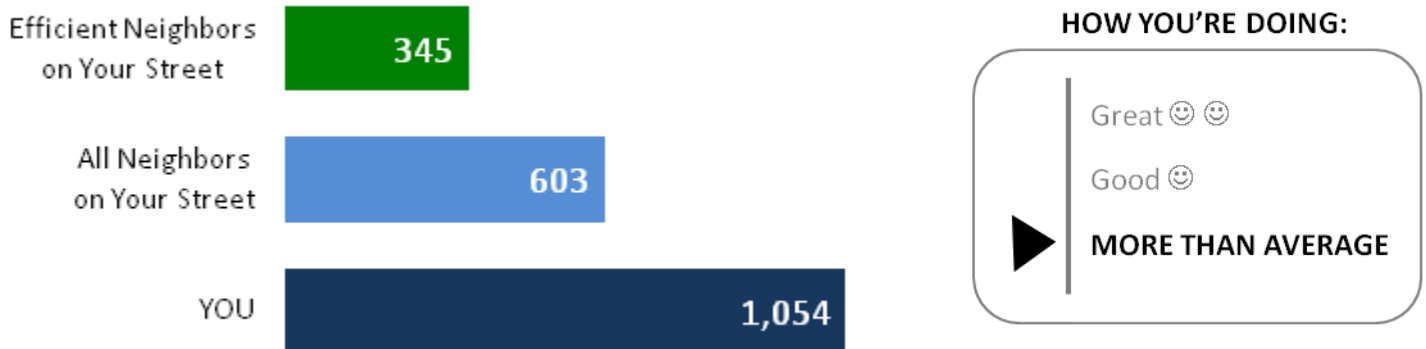
- Check to see that windows and doors are closed when cooling your home.
- Raise the temperature setting on your thermostat when your home is unoccupied.
- Turn things off when you are not in the room such as lights, TVs, entertainment systems, and computers.
- Plug home electronics, such as TVs and DVD players, into power strips; turn the power strips off when the equipment is not in use—TVs and DVDs in standby mode still use several watts of power.

# Home Energy Report

for

2021B Bedford Drive

**June 2012 Household Comparison** | You used **75% MORE** electricity than neighbors on your street.



Note: The above numbers are normalized for home size and represent monthly electricity usage per square foot (watt-hr/ft<sup>2</sup>).

## WHO ARE YOUR "NEIGHBORS"?

**"All Neighbors":** All the homes on your street that were occupied for all of last month.

**"Efficient Neighbors":** The most efficient 20% of all the homes on your street that were occupied for all of last month.

## TIPS TO SAVE ENERGY IN JULY

- Check to see that windows and doors are closed when cooling your home.
- Raise the temperature setting on your thermostat when your home is unoccupied.
- Turn things off when you are not in the room such as lights, TVs, entertainment systems, and computers.
- Plug home electronics, such as TVs and DVD players, into power strips; turn the power strips off when the equipment is not in use—TVs and DVDs in standby mode still use several watts of power.

## Appendix C: Stata Regression Output for Home Energy Report Experiment

```
. reg differencefromjune squarefeet cdd i.neighborhoodnumber i.unittypenumber i.experimentgroup
> p, cluster(homeid) robust
```

Linear regression

Number of obs = 1425  
 F( 17, 474) = 89.28  
 Prob > F = 0.0000  
 R-squared = 0.4583  
 Root MSE = 250.94

(Std. Err. adjusted for 475 clusters in homeid)

differencefromjune	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
squarefeet	-.1186182	.0746243	-1.59	0.113	-.2652535	.0280172
cdd	1.442203	.0379716	37.98	0.000	1.367589	1.516816
neighborhoodnumber						
2	40.91437	60.90197	0.67	0.502	-78.75687	160.5856
3	-111.2556	115.0723	-0.97	0.334	-337.3704	114.8593
4	-42.38705	110.7766	-0.38	0.702	-260.0611	175.287
5	-62.55049	74.17654	-0.84	0.400	-208.306	83.20503
6	-59.76036	96.31526	-0.62	0.535	-249.018	129.4973
7	-4.296832	134.2456	-0.03	0.974	-268.0869	259.4932
8	-188.9319	113.3101	-1.67	0.096	-411.5842	33.72028
9	-92.36241	87.8525	-1.05	0.294	-264.9909	80.26612
10	-14.63331	129.4178	-0.11	0.910	-268.9368	239.6702
11	-26.5119	102.3812	-0.26	0.796	-227.689	174.6652
unittypenumber						
2	34.54905	31.29746	1.10	0.270	-26.94988	96.04798
3	96.97934	50.34956	1.93	0.055	-1.956611	195.9153
experimentgroup						
1	-46.94886	34.95498	-1.34	0.180	-115.6347	21.73702
2	-60.33847	26.76413	-2.25	0.025	-112.9295	-7.747441
3	-34.68978	24.09741	-1.44	0.151	-82.04074	12.66117
_cons	-170.6	203.895	-0.84	0.403	-571.2498	230.0498

## Appendix D: Stata Regression Output for Normative-Based Billing Analysis

```
. reg totalkbtu sqfeet hdd cdd i.livebilling i.housetypenumber i.villagenumber,
> cluster(familyid) robust
```

Linear regression

```
Number of obs = 18216
F( 13, 1621) = 798.53
Prob > F      = 0.0000
R-squared     = 0.6266
Root MSE     = 2065.6
```

(Std. Err. adjusted for 1622 clusters in familyid)

totalkbtu	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
sqfeet	3.652766	.1967886	18.56	0.000	3.26678	4.038753
hdd	9.079375	.0999249	90.86	0.000	8.88338	9.275371
cdd	7.371486	.159431	46.24	0.000	7.058773	7.684198
1.livebilling	-1091.137	49.86629	-21.88	0.000	-1188.946	-993.3281
housetypenu~r						
2	816.1772	131.9676	6.18	0.000	557.3323	1075.022
3	1882.202	150.8198	12.48	0.000	1586.38	2178.024
villagenumber						
2	-410.5606	131.6581	-3.12	0.002	-668.7986	-152.3226
3	-1991.038	205.91	-9.67	0.000	-2394.915	-1587.16
4	-1544.14	120.9118	-12.77	0.000	-1781.3	-1306.98
5	-1161.198	159.3362	-7.29	0.000	-1473.724	-848.6712
6	-1550.945	275.9082	-5.62	0.000	-2092.119	-1009.771
7	-1964.743	227.0833	-8.65	0.000	-2410.151	-1519.335
8	-2444.807	288.5148	-8.47	0.000	-3010.708	-1878.906
_cons	-1987.623	328.7536	-6.05	0.000	-2632.45	-1342.796

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