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PAY-AS-YOU-GO ELECTRICITY: THE IMPACT OF PREPAY PROGRAMS ON ELECTRICITY CONSUMPTION

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THESIS

A thesis submitted in partial fulfillment of the requirements for
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By

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ABSTRACT OF THESIS

PAY-AS-YOU-GO ELECTRICITY:
THE IMPACT OF PREPAY PROGRAMS ON ELECTRICITY CONSUMPTION

Prepay or pay-as-you-go programs are an increasingly popular type of rate plan offered by electric utilities. Under these plans, ratepayers must keep a positive balance at all times to avoid being automatically disconnected, they are charged daily for their usage, and they are provided with a means to monitor their consumption. One of the suggested benefits of these plans is that they allow electricity consumers to better manage their usage. Using household level monthly usage data from customers enrolled in prepay programs at two Kentucky rural electric cooperatives, we investigate whether there is a change in consumption after these customers enrolled in the program. To address this question, we employ a fixed-effects model. The results of our model indicate that prepay customers reduce their consumption by an average of 11% after enrolling in the program. We also find that this response is larger during periods of high or low temperatures than during mild weather. Furthermore, we find evidence that the prepayment effect diminishes over the length of time that a customer is enrolled in the program.

KEYWORDS: Electricity, prepay, billing method, feedback, fixed-effects, bounded rationality

William M Martin

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Chapter 1 Introduction

Household energy demand has been an important topic of interest within the field of economics for decades. In the 1970s, the backdrop was the oil embargo and the need to conserve energy to reduce dependence on foreign oil (Abrahamse, Steg, Vlek, & Rothengatter, 2005). Today, the focus is still on conservation, but the main motivating factors have changed. While there are still concerns about resource scarcity and national security, climate change and environmental regulations have renewed interests in modeling household energy demand. The end goal of these studies is often to determine methods to that can enable or encourage households to reduce their energy consumption. It is increasingly understood that behavioral psychology needs to be incorporated into how one understands energy demand. An often-ignored aspect this part of the literature, however, is how the billing method can impact that behavior.

Most U.S. households receive a bill at the end of the month that tells them how much electricity they have consumed and how much they owe for that electricity. Prepay or pay-as-you-go rate structures are increasingly seen as an attractive alternative to this traditional postpay method. Unlike monthly billing, prepay customers pay in advance and they are continuously notified of their electricity use. Even though the rate one pays for electricity does not change with the new billing method, many argue that prepay plans cause consumers to use less electricity (Carter & Claywell, 2014; Day & Slobada, 2013; Lakes, 2014; McCoun, 2014; Ozog, 2013; R.W. Beck, 2009). The effect is typically attributed to the idea that customers become more aware of their electricity consumption after enrolling in prepay plans.

The purpose of this analysis is twofold. First, we develop a theoretical framework that attempts to explain why prepay rates might alter electricity consumption. We then use a sample of household electricity consumption data to empirically investigate this relationship. Based on previous work that looks at the importance of feedback on one's electricity consumption behavior, we hypothesize that the households in our sample will show a significant reduction in usage after enrolling into a prepay plan.

Our sample data are from two rural electric cooperative corporations (RECCs) in central and eastern Kentucky. The data is limited in the sense that it contains no household-level characteristics, such as size of residence or type of heating used. This necessitates that we do an ex-post analysis on households that switch from postpay to prepay as opposed to comparing the prepay sample to the postpay sample. The fixed effects model employed in this analysis captures many of the determinants of electricity consumption in the fixed effect error term. It allows us to focus on the change in billing method, our variable of interest. This paper contributes to the literature because it uses a unique data set for the empirical analysis, and it is the first study to propose a theoretical framework for how billing method can impact consumption.

The literature identifies numerous factors that determine household electricity consumption. This study does not attempt to catalog all of those factors, nor does it attempt to replace their significance. The goal of this paper is to add to the literature by identifying an additional behavioral factor that could impact household electricity consumption. This kind of information is of increasing relevance to energy system modelers who can use this improved understanding of consumer behavior to help build better bottom-up energy system models.

There are important practical implications to determining whether the billing method used can impact one's electricity consumption. Policy makers could theoretically use prepay plans as a low-cost means to lower residential consumption, reducing the negative externalities associated with electricity consumption. Typically, this kind of demand-side management (DSM) has focused on providing consumers with incentives to engage in energy-saving behavior. Prepay rates are important in this respect because they have the same end-effect of these policies, but they do so at a fraction of the cost. See Allcott and Greenstone (2012) for a discussion on the cost-effectiveness of conservation programs (Allcott & Greenstone, 2012).

The paper proceeds as follows: Chapter two provides a description of how prepay plans typically work, a brief history of their implementation, and a detailed description of the specific program characteristics for the cooperatives studies in this analysis. In chapter three we provide a theoretical framework for the demand for energy services and how a different payment plan can alter consumer behavior. Chapter four describes the data collection process and the descriptive statistics for the sample used in the analysis. In chapter five, we describe the empirical models employed in the analysis, and chapter six provides the results of those models with brief interpretations of their meanings. Finally, chapter seven summarizes the study's findings and describes some of the larger implications of the results.

Chapter 2 Study Background

2.1 Prepay Rates

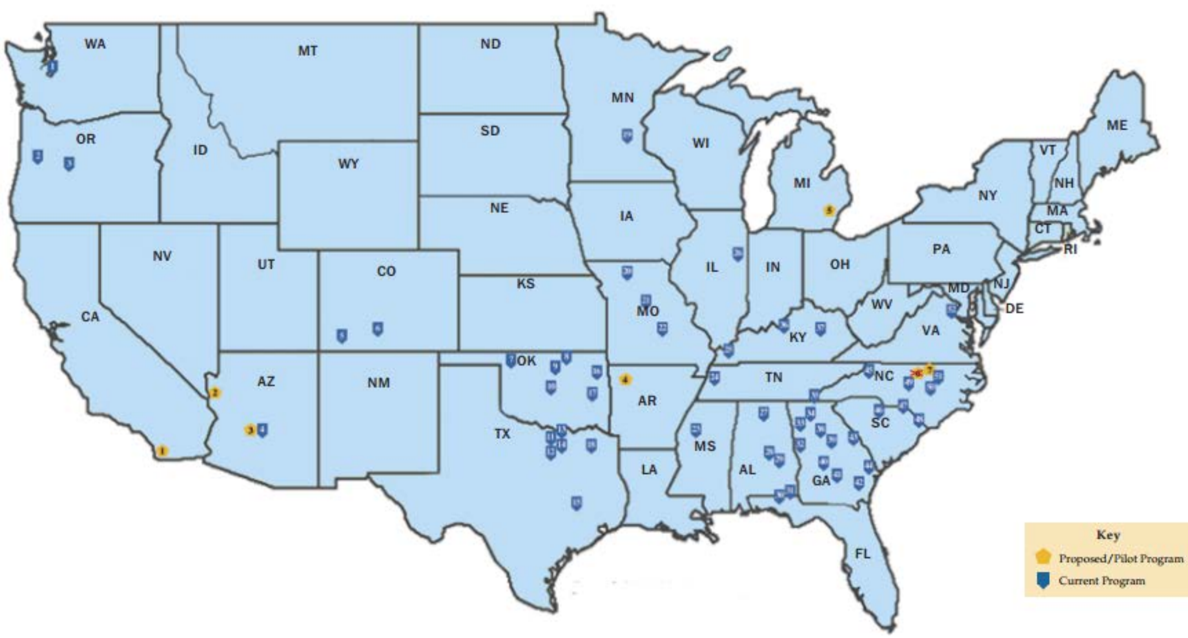
In the United States, nearly all residential electricity is purchased on a monthly billing cycle. Consumers are charged a fixed fee and a charge based on the amount of electricity (kWhs) that they consume in a given month. Most consumers are thus unaware of how much electricity they consume until their bill arrives. Because consumption occurs in advance of billing, electricity providers are at risk from non-payment. So, to ensure that new customers will be able to reliably pay their bills, electric utilities typically charge a deposit that can be collected when a customer fails to make their payments. They also have the ability to disconnect service for consumers who continue to fall behind on payments. This disconnection, however, often occurs weeks or months after the consumer initially falls behind on payments.

Prepay or pay-as-you-go rate structures are increasingly seen as an attractive alternative to this traditional postpay method. Unlike monthly billing, prepay customers pay in advance and they are continuously notified of their electricity use. These plans usually require little or no deposit because the electricity will be disconnected before the customer is able to incur a negative balance. One illustrative comparison that is often used to describe prepay plans is that it is a similar process to paying for gasoline for one's vehicle. Putting money into one's prepay account is like filling up the tank. You decide how much you would like to buy and can afford, and then you purchase the fuel in advance. In both cases, you have a way to see how much fuel or electricity you have left so that you can keep from running out. Just as no one wants to be stuck on the side of the road with no gas, prepay customers have a strong incentive to maintain a positive balance so their electricity is not disconnected.

The idea of paying in advance to use electricity is not new. Coin-operated electricity meters have been around since 1901, and they remained common in the United Kingdom until the mid-1980s (Cox, 1901; Owen & Ward, 2010). Until recently, adopting prepay required utilities to install a specialized meter at each prepay household. Often, these meters use *smartcards*, which function similarly to a long-distance phone card. Consumers can add money to the card at various locations, and a unit at the meter or in the house can tell them how much money remains. Viewed by many utilities as overly expensive and cumbersome, these systems never caught on in many countries.

The increasing availability of *smart* or *advanced metering infrastructure* (AMI) *meters* has brought renewed interest to prepay (R.W. Beck, 2009). In most cases, these meters are not installed for the purpose of implementing prepay programs. Utilities typically install AMI systems because they increase meter accuracy, reduce maintenance costs, and better outage management. Once AMI meters are installed, however, implementing a prepay system becomes much less capital-intensive than the old card-reader systems, and two-way communication at the meter allows the utility to have a more detailed picture of customer usage. The consumer also benefits with AMI, as it often allows them to pay for electricity online or over the phone. In many cases, it also gives them the ability to see a much more detailed picture of their electricity usage (R.W. Beck, 2009).

Figure 2.1 Current and Proposed Prepaid Electric Programs in the US[1]



[1] Image from Howatt (2012). Image is Current as of March 31, 2012.

Researchers estimated that about 23 million people worldwide use some form of prepay rate plan to pay for electricity (Martin, 2012). In the U.K. alone, there are over 4 million customers, or about 15 percent of households, that prepay for electricity (Rocha, Baddeley, & Pollitt, 2013). In the U.S., that number is much lower. A report from 2009 estimated that there were roughly 100,000 U.S. customers enrolled in a prepay plan (R.W. Beck, 2009). However, with rising electricity rates, faster communication speeds, and an increasing prevalence of AMI technology, this number is expected to grow rapidly, and is most likely already out of date. Figure 2.1 shows the locations of utilities that currently have plans to implement prepay rates (Howat, 2012**)**. Traditionally, municipal utilities and rural electric co-ops have been the first utilities to adopt prepay[2], but a newly approved trial by a Kansas Investor Owner Utility (IOU) could signal a significant expansion of the programs (Tomich, 2014). One survey, for example, found that 38 percent of electric utilities are considering prepay rates (Howat, 2012).

Utilities have various motivations for implementing prepay programs. Many see the primary benefit as a way to limit write-offs from bad debt as well as simply increasing the predictability of their cash-flow. Because of the time value of money, a better cash-flow can improve profits. This is only a benefit, however, in terms of their relationship with customers that had previous problems with late-payments. It could be argued that the utilities benefit from offering both prepay and postpay because they each maximize revenue from a different customer class. Another oft-stated benefit is that it has the potential to reduce operating costs as the automatic disconnect implies that a crew is not required to go out and manually disconnect service. Some utility employees also argue that the program can improve the relationship between customers and the utility. As customers become more aware of their usage patterns, they are less surprised by high costs during certain times of the year. One utility employee noted that consumers who once felt cheated by the utility, now come into the office to ask for advice on how to lower their usage (McCoun, 2014). Because of these benefits, some argue that utilities could charge the same or lower rate to prepay customers. Typically, however, there is a fee, which is justified to regulators based on the initial capital expenditures and increased payment processing.

[2] See section 2.2 for more information on rural electric cooperatives.

For customers, potential benefits of prepay rates can be divided into two categories. On the one hand, there are some immediate and direct benefits, which depend on the specifics of the individual utilities. One of the most common of these benefits is that prepay plans often include no deposit. For new customers, especially those with poor credit and low incomes, this can be an enticing benefit. Additional direct benefits might include the elimination of late payments and the subsequent late payment fees. Many utilities also eliminate disconnect and reconnect fees for prepay customers. These benefits only apply to customers who have trouble keeping up with payments, but for those customers, it can add up to a sizeable savings. The Electric Power Research Institute (EPRI) found that "financially troubled" customers save 20% on their electricity expenditures because of a reduction in late fees and reconnection fees as well as reductions in consumption (R.W. Beck, 2009).

The other proposed benefits to prepay are more indirect, but they are commonly referred to as the main motivation behind implementing a prepay program. Those benefits have to do with how prepay rates can impact consumer behavior. Several researchers have argued that prepayment causes consumers to be more aware of their energy use, and furthermore, it gives them the incentives and awareness needed to reduce their consumption (Carter & Claywell, 2014; Lakes, 2014; McCoun, 2014; Owen & Ward, 2010; R.W. Beck, 2009; Villarreal, 2012). Evidence from industry studies backs up this idea, showing that consumers that switch from postpay to prepay reduce consumption by 10-18% (Day & Slobada, 2013; Owen & Ward, 2010; Ozog, 2013; R.W. Beck, 2009; Villarreal, 2012). This opportunity to more effectively control consumption allows consumers to budget and lower their total expenses.

Prepayment plans are not without criticisms. Many consumer advocates are adamantly opposed to the rate structure, while others believe that they must be implemented with tight restrictions. Common arguments are that the plans add fees[3], that they bypass consumer protections, making it easier to disconnect someone's electricity, and that they target low-income consumers, creating a "second-class" of utility customers (Garthwaite, 2014; Howat, 2012; Villarreal, 2012). In many cases in the U.S., these arguments have been effective at preventing the implementation of prepay programs. Public service

[3] Most prepay plans include a monthly program fee.

commissions (PSCs) and state attorneys general from Massachusetts to California have sided with the consumer arguments, worried that the new plans will indeed undo consumer protections (Garthwaite, 2014; Howat, 2012; Owen & Ward, 2010; Villarreal, 2012). Critics argue with the premise that the prepayment plans reduce consumption, stating that choosing to go without a necessary service is not the same as "savings." One Sierra Club representative referred to this effect as "deprivation, not conservation" (Garthwaite, 2014). All of these criticisms fail to take into account, however, the fact that consumers (especially those with a constrained income) often have fewer fees with prepay because they are unable to build new debt. More importantly, they do not address the fact that customer surveys repeatedly show that prepay customers prefer prepay plans to postpay plans (Day & Slobada, 2013; Owen & Ward, 2010; R.W. Beck, 2009; Villarreal, 2012). As further evidence of this preference, customers that voluntarily sign up for prepay plans rarely switch back to postpay (Day & Slobada, 2013).

One thing that proponents and critics alike agree on is that prepay will become increasingly common in the future. As mentioned earlier, the increasing availability of AMI meters will make it a more feasible option in countries like the U.S. An even larger growth opportunity, however, is in the developing world where consumers will often go from no access to electricity to access through prepayment (Garthwaite, 2014). Prepay service was launched on Haiti's southern peninsula in 2012, for example, to help people move from "candles and kerosene to grid electricity"(Garthwaite, 2014). Navigant, a large research and consulting firm, estimates that the number of prepay meters installed worldwide will quickly rise to 33 million by 2017 (Martin, 2012).

2.2 Prepay in Kentucky

Many of the first utilities to implement prepay plans in the U.S. have been rural electric cooperatives. See figure 2.1 for a map of utilities that have implemented prepay programs. These cooperatives are private, non-profit utilities that are owned by the customers that they serve (NRECA, 2014)[4]. Following this trend, the first Kentucky utilities to adopt prepay have all been Rural Electric Cooperative Corporations (RECCs). Some argue that cooperatives have been the earliest adopters of prepay programs because they are not subject to the full regulatory authority of public service commissions (Howat, 2012). However, the RECCs in Kentucky are under the jurisdiction of the state PSC, which approved all of the new prepay tariffs. A more likely reason that investor-owned utilities (IOUs) have shied away from prepay plans is that they fear the impact the program could have on their public profile if it was strongly opposed by consumer advocates, as has been the case in many areas (R.W. Beck, 2009). Another important factor is that rural cooperatives are, by design, focused on residential energy sales (NRECA, 2014). In Kentucky, the RECCs are either retailers (distribution) or wholesalers (the co-ops that generate and transmit the power). The distribution RECCs have some incentive to reduce consumption because they have to buy it from the generation and transmission (G&T) co-ops. They also typically have few commercial and even fewer industrial customers. Therefore, when a service territory has a large number of residential customers that struggle to pay their bills, the co-op has a large incentive to restructure its payment system.

This paper contains data from two RECCs in Kentucky that have recently adopted a prepay tariff: Jackson Electric and Bluegrass Electric. Figure 2.2 shows the location of the co-ops' service territories. Jackson Electric was the first of the two and the first utility in Kentucky to adopt the prepay tariff. In many ways, they paved the way for other co-ops in the state to adopt the program. Jackson had to navigate the concerns of the Public Service Commission, and they faced the most uncertainty on how their customers would respond. They were not, however, totally in the dark. They modeled much of their program after other RECCs, such as Brunswick Electric in North Carolina. By the time Jackson initiated its new tariff, prepay programs were common enough that they were already a built-in-option with many of the utility software providers.

[4] There are generation and transmission (G&T) coops as well as distribution coops. However, when we refer to cooperatives in this paper, we will only be discussing distribution coops as these are the utilities that sell the power to residential customers.

Figure 2.2 Blue Grass Energy and Jackson Energy Service Territories[5]

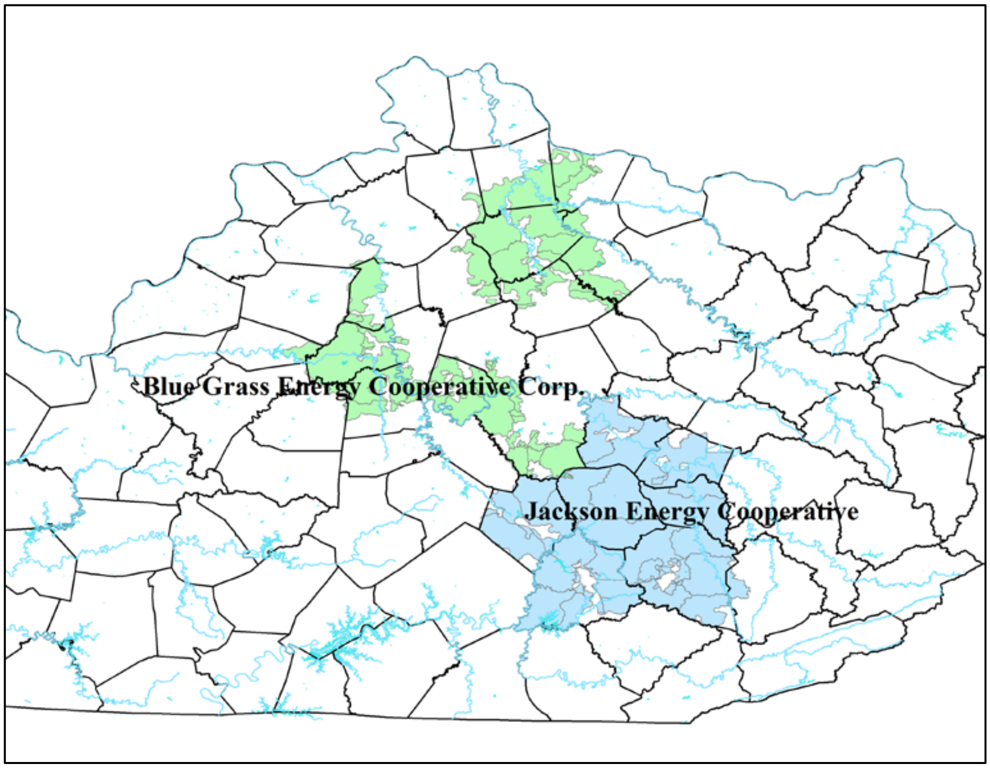


Table 2.1 describes the economic and housing characteristics for each of the RECCs. These descriptive statistics are important because they help paint a picture of the population being impacted by the new programs. The individual cooperatives do not maintain housing or economic data on their members, so all of the statistics listed in the table are an approximation of the customer base for each utility[6]. The co-op service territories are alike in many ways. Beyond the fact that they all represent rural areas in Kentucky, it is also important to note that they all have a higher than average number of customers that use electricity as their primary heating fuel. Space heating makes up about 41% of the average U.S. household's energy consumption, so areas that use electricity for heat tend to have much higher electricity bills (EIA, 2013). In many ways, however, Bluegrass Energy stands out from the other two co-ops in that its customers are much more representative of the state as a whole. Both Jackson

[5] Shape files downloaded from the Kentucky Public Service Commission.

[6] Zip-code level data from the 2012 American Community Survey were used. All zip-codes that fell within one of the service territory boundaries were aggregated together. Often, zip-codes fall within multiple service territories. Therefore, these descriptions are not exact, but they are useful in providing a relative comparison to the state as a whole.

Energy and Farmers RECC, on the other hand, have a higher than average percentage of mobile homes[7], higher unemployment, and lower average incomes than the state average (U.S. Census Bureau, 2012).

Each of the co-ops' prepay programs are very similar in structure (See table 2.2). They are all voluntary, they all have a small monthly fee which is pro-rated on a daily basis, and they all provide some sort of energy-use feedback. The plans differ some in the size of their monthly fees as well as how they provide feedback to the customer. Jackson, for example, opted to provide an in-home-display (IHD) for all prepay customers (see figure 2.3) while bluegrass uses text, email, and phone alerts (see figure 2.4). Additionally, while both of these prepay plans are based on the utility's traditional residential rate, these rates vary significantly among the utilities. Jackson Energy has a higher energy charge and higher monthly fixed charge, but Bluegrass has a higher prepay program fee. Another important distinction is that Jackson Energy charges a transaction fee for each payment made onto one's prepay account, providing a disincentive for making numerous, small payments. Combining median incomes from table 2.1 with average energy usage and costs from table 2.2, we estimate that electricity costs require an average of 3% of total household income for Bluegrass customers and roughly 5% for Jackson customers. If one assumes that customers that enroll in prepay programs have lower incomes, on average, then electricity costs are likely taking up an even larger share of their budget.

Beyond the mechanics of the rate, these three prepay programs are all very similar in their stated objectives. In interviews conducted with managers at each of the cooperatives, the author found that they all see prepay as a means to prevent customers from accruing large debt loads, hoping to eventually lower the amount of debt that the co-op has to write-off. They all stated, however, that the most important motivation for implementing the prepay program was to give customers more information, so that they can better manage their usage to stay within the confines of their budgets. Each of the cooperatives expects that customers that switch from postpay to prepay will, on average, reduce their energy

[7] Mobile homes, especially those produced before 1976, are often poorly insulated. Per square foot, these older mobile homes consume 53% more energy than other types of housing (Environmental and Energy Study Institute, 2009).

consumption, but they are unclear on the magnitude of this change (Carter & Claywell, 2014; Lakes, 2014; McCoun, 2014).

2.3 Data Collection

One of the strengths of this study is the unique data set that was acquired.

In order to find appropriate data to study prepay rates, contact was first made with the Kentucky Association of Electric Cooperatives (KAEC). After discussing the issue, KAEC suggested that some of the state's electric cooperatives that had implemented prepay programs might be willing to share customer usage data. KAEC and the researchers then agreed on three electric cooperatives in the state that would be representative of the new program. Jackson Electric was chosen because it was the first co-op in the state to implement a prepay program, and it had the largest sample of prepay customers. Bluegrass Electric was also chosen because of its relatively large number of customers. Farmers RECC was chosen to provide even more diversity to the total sample. The feeling was that these three co-ops were a good representation of the varying demographic profiles of the co-ops in the state (see chapter 2). KAEC then introduced the project idea and the researchers to representatives at each of the three coops. It is unlikely that the researchers would have been able to obtain household level data from the co-ops without the help of the KAEC.

All three co-ops generously agreed to provide household-level electricity consumption data. Due to technical difficulties, however, Farmers RECC was unable to gather the information in time for the publication of this study. While requiring considerable back-and-forth communication, the other two utilities were able to put together large data sets of prepay and postpay customers that could be used in the empirical analysis. The researchers also desired descriptive information about the customers as well as their housing type. This would have made it possible to compare the sample of prepay customers to the larger population of co-op members. The co-ops, however, do not keep this kind of information. Household addresses would have allowed the researchers to find housing characteristics through county property tax databases, but the co-ops are unable to share addresses because of state and federal privacy protection rules. In addition to quantitative data, the cooperatives were also extremely helpful in providing descriptive information about the programs. The researchers conducted interviews with program managers at each of the co-ops, which later informed much of the content for chapter 2.

Table 2.1 Demographic Characteristics

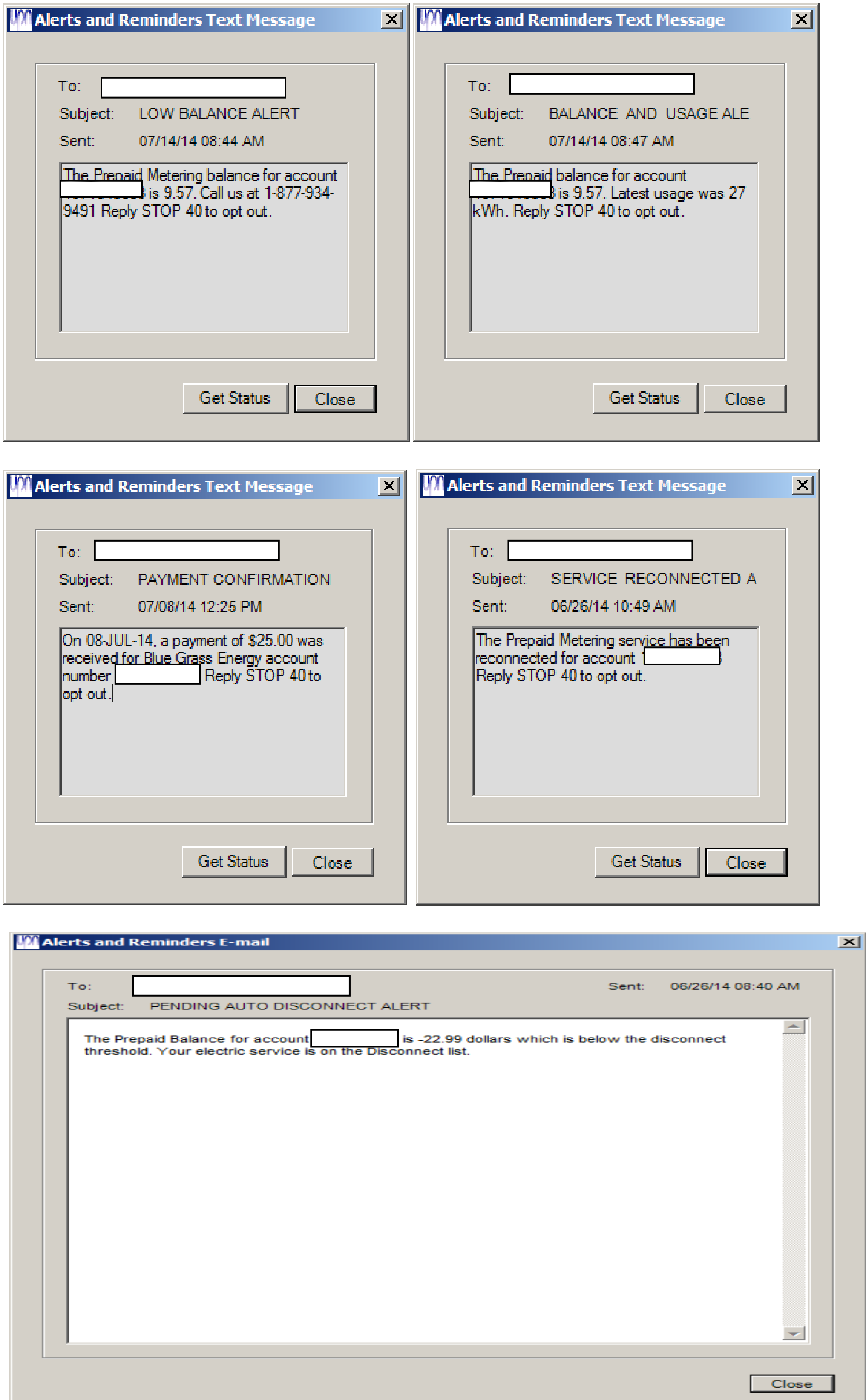
	Bluegrass	Jackson	KY
Total Housing Units	195,538	108,907	1,927,916
Mobile Home %	7.93%	20.85%	12.50%
Construction year of home			
2011 or Later	0.47%	0.40%	0.30%
2000 to 2009	16.83%	14.37%	14.20%
1990 to 1999	20.47%	20.77%	17.60%
1980 to 1989	16.39%	17.18%	13.30%
1970 to 1979	17.20%	17.38%	17.10%
1960 to 1969	9.40%	11.92%	11.50%
1950 to 1959	6.92%	7.63%	9.90%
1940 to 1949	3.05%	3.88%	5.00%
1939 or earlier	9.27%	6.48%	11.10%
Housing Tenure			
Occupied Housing Units	176,052	94,952	1,691,716
Renter Occupied	34.89%	31.57%	31.00%
Owner Occupied	65.11%	68.43%	68.03%
Primary Heating Fuel			
Occupied Housing Units	176,052	94,952	1,691,716
Utility Gas	29.18%	23.66%	39.50%
Electric	60.60%	62.72%	49.00%
Other Fuel	9.99%	12.69%	11.37%
No Fuel	0.14%	0.11%	0.18%
Median Home Value*	$142,602	$98,695	$120,000
Employment			
Civ. Labor Force	230,793	106,641	2,054,159
Unemployed	8.61%	11.49%	9.50%
Income			
Median Household Income*	$46,262	$30,311	$42,610
Total households	176,052	94,952	1,691,716
Under$15,000	15.06%	23.37%	17.40%
$15,000 - $34,999	22.40%	28.08%	24.80%
$35,000 - $74,999	34.30%	30.66%	32.40%
$75,000 - $149,999	22.90%	15.14%	20.60%
Greater than $150,000	5.36%	2.75%	4.90%
Households Receiving SSI	5.37%	10.24%	7.10%
***average weighted mean of median by zip code**			

Table 2.2 Prepay Program Characteristics

	Bluegrass	**Jackson**
Total Residential Members (As of July 1, 2014)	55,000	51,240
Total Prepay Customers (As of July 1, 2014)	1,450	3,000
Percentage of members	2.64%	5.85%
Total Prepay Customers after first 6 months	550	1,222
Average monthly residential Usage in 2013 (kwh)	1,253	1,228
# of customers who switch back from prepay to post pay	42	27
First day prepay program was available to customers	9/17/2012	6/27/2011
Customer Charge (Monthly fixed fee for all customers)	$9.73/ month	$10.44/ month
Program Fee (Monthly fixed fee for prepay customers)	$8.75/ month	$5.00/ month
Daily base charge (Total fixed fees/30)	$0.62	$0.51
Energy Charge ($/KWh)	$0.08951	$0.09849
Transaction Fee	$0.00	$1.25
In Home Display (IHD) provided?	No	Yes
Cell Phone Alerts	Yes	Yes
Email alerts	Yes	No
Prepay Contract Length	1 year	No contract
Avoided Fees		
Average Deposit Required	$225	$400
Late Fee Charge	7.50%	5%
Reconnection Fee	$50/ $75 after hours	$25

Figure 2.3 In-Home Display (IHD) Used by Jackson Electric

Figure 2.4 Sample Text Message Alerts for Prepay Account Holders



Chapter 3 Theoretical Model

Both economic and psychological factors significantly impact household consumption decisions. This section outlines a theoretical framework that demonstrates how consumption decisions are impacted by the way in which consumers pay (such as prepayment or postpayment) and the information they have available. This theory provides the framework and a guide for the empirical analysis.

3.1 A Metaphor

Consider the amount of gas a family purchases for their car. How much will they purchase? It is mostly a function of how far they want to drive, how efficiently their vehicle uses gas, and how they choose to drive the vehicle. However, are there other behavioral factors that impact how much gas they choose to purchase? Does it matter that we can watch the price go up as we fill up our tank? Does it matter that we must pay for our fuel before using it? And does it matter that there is a consequence to letting that fuel run out? It's strange to image a situation in which we could drive our car as much as we like, not knowing how much gas we're consuming, and not being charged for that gas until the end of the month, yet that's almost exactly how most of us pay for electricity. The following section details the economic theory on why the method of payment might impact one's consumption decisions.

3.2 Residential Electricity Demand Model:

Individuals consume electricity in order to produce various residential services (lighting, cooking, entertainment, heating, etc.). In that sense, any demand model for residential electricity consumption is a derived demand for the specific services provided by electricity. The model must, therefore, account for the interactive demands between energy using capital (i.e. appliances) and the energy used by that capital (i.e. electricity) (Lakshmanan & Anderson, 1980).

Economists have been analyzing this derived demand for electricity consumption for at least 63 years, starting with Houthakker in 1951 (Houthakker, 1951). Lakshmanan and Anderson built on the work foundational of Houthakker, and provided us with our initial framework for a static equilibrium model of residential energy use (1980). In the short-run, we assume that a residential consumer's ability to change their energy consuming capital stock is fixed[8]. Their demand for electricity is simply a function of its price, the price of substitute fuels, household income, residential characteristics, and weather (Lakshmanan & Anderson, 1980). In this model, a consumer with a fixed budget can only respond to price increases or extreme weather by lowering their demand for energy services. This would include actions such as turning off lights, lowering the thermostat, or adjusting the temperature of the water heater.

For individual consumers, *i*, we specify the above static equilibrium model as follows:

Equation 3.1

$$Q^*_{ijt} = f(Y_{ijt}, PE_{jt}, PS_{jt}, W_{jt})$$

Where:

i= The individual consumer/household

j = The geographic location of the consumer (In this case, their utility service territory).

t = The *t*th month

Q^*_{ijt} = The quantity of energy demanded in month *t*

Y_{ijt} = The income of household *I* in month *t*

PE_{jt} = The price of electricity in location *j* in month *t*

PS_{jt} = The price of substitute fuels in location *j* in month *t*

W_{jt} = The weather and climate conditions in location *j* in month *t*

Numerous studies have used a similar framework to assess the determinants of residential energy consumption. Many of these focus on the characteristics of the *i* households. Brounan, Kok, and Quigley, for example, identify nine physical characteristics[9] and ten demographics characteristics[10] that all have a significant impact on a household’s energy consumption (Brounen, Kok, & Quigley, 2012).

[8] The long-run, of course, presents the consumer with different options. They can, for instance, purchase appliances that produce the same energy service with less energy.

[9] The nine physical characteristics are dwelling type, period of construction, historic structure, dwelling size, number of rooms, central heating, maintenance interior, maintenance exterior, and insulation quality.

[10] The ten demographic characteristics are number of persons in household, age of head of household, single person household, household with children, age of oldest child, number of children, elderly household, fraction of females in household, occupied by foreign born, and household income.

Other studies, such as Costa and Kahn (2013), have shown that even ideological factors can determine a household's electricity consumption.

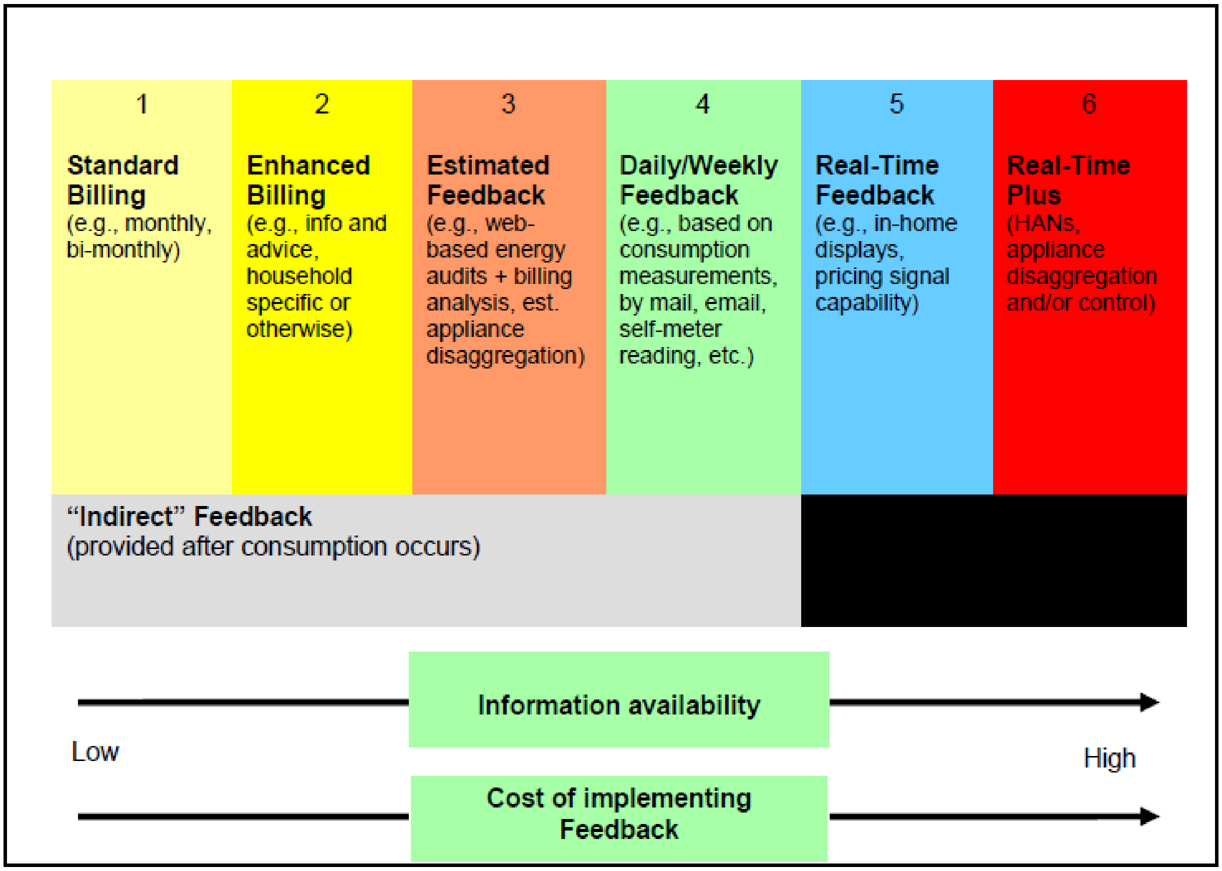
Including these demographic, household, and ideological characteristics helps researchers identify the energy service preferences of the given household, providing a more complete model of residential electricity consumption. Costa and Kahn summarize this model as follows: Consumers demand various energy services for which electricity is an input. One's total electricity consumption in a given period is a sum of the electricity required for each of those services. This consumption depends on choices over 1) the physical attributes of the house such as its size and age; 2) the attributes of the appliances (which convert electricity into energy services); and 3) the amount one choses to use those appliances. All of these choices, in turn, are shaped by climate, prices, income, and characteristics of the household (demographics and ideology) (Costa & Kahn, 2013).

All of the models described above are based on a neoclassical economic framework, assuming that consumers are utility-maximizing, rational individuals with perfect information. Given those assumptions, the payment structure (i.e. Prepay rate plans) should have no effect on one's demand for electricity. Many other schools of economic literature, however, argue that there are behavioral factors that must be considered. In the ensuing sections, we will describe some of the factors that cause consumer decision making to deviate from the classical economic framework of optimality.

3.3 The Role of Information:

Many have argued that energy is essentially invisible to the typical consumer (Hargreaves, Nye, & Burgess, 2010). First, it is a physically invisible commodity, entering the house through often hidden wires. More importantly, however, energy consuming actions are often "inconspicuous routines and habits," and consumers have a difficult time connecting energy use to specific actions (Hargreaves et al., 2010). Consumers have never been entirely blind when it comes to information on their energy usage, it's just that this information has typically been delayed or labor intensive to acquire. One can use the previous month's bill, for example, to predict the current month's usage. Another option has been to check the outside electrical meter, record the total usage, and monitor how it changes. A much more effective/realistic approach, however, is to provide some sort of direct feedback[11] (see figure 3.2.1) to the consumer.

Figure 3.1 Types of Feedback for Electricity Usage



(Ehrhardt-Martinez, Donnelly, & Laitner, 2010)

Economists and other behavioral scientists have been analyzing the impact of information feedback on electrical consumption since the late 1970s. These early behavioral science studies found feedback can lead to significant reductions in electricity consumption (Bittle, Valesano, & Thaler, 1979; Hayes & Cone, 1981; Winett, Neale, & Grier, 1979). More recent economic studies have found similar results, often using much larger sample sizes and more rigorous techniques. In a review of the feedback literature, Darby found that direct feedback leads to a reduction of five to fifteen percent (Darby, 2006).

[11] Direct feedback is typically defined as being nearly instantaneous and easy to comprehend (Darby, 2006).

Another study did a controlled experiment, looking specifically at the impact of electricity usage feedback by means of text messages (the feedback method employed by two of the three utilities analyzed in this study) and found that they led to a three percent reduction (Gleerup, Larsen, Leth-Petersen, & Togeby, 2010). Many recent studies, however, urge caution in assuming any long-term reduction in consumption, arguing that any effects of feedback diminish over time (Abrahamse et al., 2005; Gleerup et al., 2010). A further complication is that there may be some interaction between the feedback and the rate structure of prepay plans. Faruqui, Sergici, and Sharif, for example, found that feedback with prepay leads to twice the level of reduction as feedback alone (Faruqui, Sergici, & Sharif, 2010).

Traditional neoclassical economic theory tells us that an electricity consumer *i* at time *t* will partake in an energy-saving action if it increases their utility, u_{it} (Ek & Söderholm, 2010). In the neoclassical sense, there is nothing about increased feedback or a prepay rate plan that should alter this utility model[12]. After all, the costs and benefits associated with the actions have not changed. We have shown, however, that there is significant evidence that feedback can alter consumption, proving that something about the model is deficient in terms of describing real world electricity usage. One school of economic literature that attempts to address this deficit is known as transaction cost economics (TCE). Similar to agency theory, TCE emphasizes asymmetric information, but it also extends the classical framework by focusing on the concept of bounded rationality and transaction costs (Prindle et al., 2007). In the context of economic theory, bounded rationality refers to consumers' limited time, attention, and ability to process complicated information. Instead of searching for "optimal" solutions, they will default to status quo actions, economizing on time and cognitive resources[13] (Simon, 1959). Essentially, these theories recognize that there is a cost to the decision-making process.

[12] Perfect information is an important assumption with neoclassical theory. We described above the ways in which consumers have had access to information on their electricity use. We suggest that this assumption is not violated, but there is a transaction cost associated with acquiring the information that is not accounted for.

[13] A related idea is the theory of *rational inattention*. This theory implies that the costs and energy involved with accurately measuring the impacts of one's behavior can be so significant that a rational consumer will ignore them. Sallee describes has this can be applied to energy efficiency (Sallee, 2013).

Many argue that bounded rationality plays an important role in the context of electricity consumption (Ek & Söderholm, 2010). In this context, consumers have a strong preference for status quo. In the case of energy consumption, that can mean consuming more than what is in their best interest in terms of utility. There are many reasons why households often stick to status quo decision-making. Behavioral science, for example, tells us that individuals have a bias towards the present situation and will often neglect future cost savings (Samuelson & Zeckhauser, 1988). Another theory that supports this idea is the omission bias, or the idea that individuals often prefer options that require no action over active decisions (Spranca, Minsk, & Baron, 1991). All of this evidence supports the idea that households have a lot of inertia working against changes in their electricity consumption routine, especially if they are unsure of the actual costs and benefits.

Information can play an important role in moving individuals closer to optimal decision-making. The right kind of information can activate cultural or social norms that might highlight the importance of electricity-saving behavior (Ek & Söderholm, 2010). More important for this analysis, however, is the idea that information can act as a nudge that can remind the consumer of the potential cost savings of behavior changes.

3.4 Planners and Doers:

Individuals who wish to lower their energy consumption in order to save money must deal with an inherent conflict between their short-term and long-term interest. One can have every intention to maximize long-run utility by lowering energy costs, but this is often in conflict with one's immediate and myopic short-term desires. Thaler and Shifren described this phenomenon by a creating a new economic theory based on our *planner* and *doer* selves (1981). Similar to the principle-agent theory of the firm, they argue that individuals have two competing sets of interest at any given time. The *doer* part of the individual is focused on maximizing near-term utility, while the *planner* is focused on long-term utility, which often means that short-term sacrifices have to be made (Thaler & Shefrin, 1981).

This theory can also be used to describe the somewhat counterintuitive idea that people often purposefully impose constraints on their future behavior in order to maximize expected utility. These constraints are often the only way that the *planner* can impact the actions of the *doer*. One way to think of voluntarily signing up for a prepay plan is that it is a type of commitment device. Essentially, one is making a second-order decision to impact their first-order decisions (Sunstein & Ullmann-Margalit, 1999). Much of the literature that emanates from the *planner-doer* model focuses on individual savings. Many have found that making a second-order decision to decrease the liquidity of a savings product[14] can prevent one from making first-order decisions (i.e. spending some of the savings) that decreases long-term utility. One would think that increased liquidity would always increase utility, but many have shown that the opposite is true when it comes to savings (Laibson, 1997; Thaler & Shefrin, 1981).

There is strong evidence that consumption increases as one's access to credit increases (Ludvigson, 1999). This is why people who wish to cut their spending are often advised to use debit cards in place of credit cards. A debit card can be thought of as a commitment device, because it limits spending to the amount of money that is currently available in their checking account. In many ways, prepay acts as a very similar type of commitment device. A postpay, monthly plan is essentially free credit from the utility that allows the consumer to easily consume as much as he or she desires. Prepay plans add the extra step of having to continually add money to one's account, forcing the consumer to make an active decision about their level of electricity usage.

[14] A Christmas savings account is a commonly used example. They are uncommon now, but these accounts often pay little or no interest and impose a penalty for early withdrawals. They were, however, very popular before the spread of credit cards.

Chapter 4 Data

4.1 Data Description

Meter-level residential energy use data was obtained from two RECCs in Central and Eastern Kentucky. The data includes customer identification numbers, monthly usage, and an indicator variable for whether or not the customer was enrolled in a prepay plan. The co-ops provided meter data for postpay customers who never enroll in prepay, customers who began as postpay and switch to prepay, and new customers that were enrolled in prepay from the beginning[15]. The empirical analysis employed in this study only looks at prepay customers that had previously been enrolled as postpay customers. The other categories are used only for comparison.

Having household level data is a major strength of this analysis. This kind of panel data creates more variability, making a more efficient estimation possible (Kennedy, 2008). It would be very difficult to conduct an informative analysis on prepay rates with only aggregate data.

When selecting customers, all three co-ops obtained previous usage history on households that were currently active co-op members at the time that the data was being collected. This was done for practical reasons, but creates a selection bias. The data does not include customers that left the service territory nor does it include customers that switched back to postpay after being enrolled in prepay. This last category, however, represents such a small number of households (see table 2.2) that its omission is insignificant. Monthly observations range from March of 2008 to July of 2014. Being that not all households were active co-op members at the same time and that each household enrolled in the program at a different time, the data are highly unbalanced. The goal was to include all months that the customer was enrolled in prepay, and at least one full year of observations prior to enrolling in the program.

The complete data set obtained from Bluegrass Energy included usage data on 1,362 prepay customers with an average of 11.7 observations per customer for a total of 15,908 observations. Jackson

[15] To avoid confusion, from this point on, “prepay” customers will refer to customers that are enrolled in the program at any point. “Enrolled” customer will refer to customers that are enrolled in a prepay program at that point in time. “Post-pay” customers will refer to customers that never enroll in prepay.

Energy provided usage data on 200 prepay customers, for a total of 9,768 observations[16] with an average of 48.8 observations per customer. Both coops also provided a small sample of postpay customers as a comparison. We also obtained a small sample of usage data on postpay customers that never enroll in a prepay program. This includes 130 customers from Bluegrass Electric and 100 customers from Jackson Electric.

Much of the data that was originally received had to be transformed or excluded from the analysis. While most of the data was provided in a monthly format, some of the original data from Jackson Electric was in the form of daily meter readings. This daily data was consolidated into a monthly format. On occasion, there were multiple observations per month for a given customer. This only occurred in the months immediately following the transition to prepay. These observations were removed because there was no way to distinguish the exact point in the month when the customer enrolled. All months with negative or zero kWh readings were also dropped.

We then generate several variables that are principle to our analysis. *Enroll* is a time-constant dummy-variable for whether a household is ever enrolled in the prepay program. *Previous History* is a time-constant dummy variable for whether a prepay household was a postpay co-op member before switching to prepay. This variable is necessary because all of our models only include data from households that have previous history with the co-op. Because descriptive data is unavailable, we attempt to isolate the prepay effect by looking only at prepay customers that had previously been enrolled as postpay customers. Finally, we generate a "Time" variable that measures the program tenure of the households. It counts the months from the households' first month of enrollment in the prepay program.

[16] Due to software limitations, Jackson Energy had to extract the data one customer at a time, thus explaining the smaller sample size.

Table 4.1 Descriptive Statistics

		Bluegrass	Jackson	Total
Electricity Consumption (kWh)				
	Mean	1,737	1,497	1,597
	Standard dev.	1,132	915	1,018
	Min	2	2	2
	Max	8,604	8,136	8,604
Monthly Avg. Cooling Degree Days				
	Mean	2.2	3.1	2.8
	Standard dev.	3.3	3.9	3.6
	Min	0	0	0
	Max	17.5	14	17.5
Monthly Avg. Heating Degree Days				
	Mean	19.5	11.8	15.0
	Standard dev.	16.1	11.6	14.2
	Min	0	0	0
	Max	45.9	36.9	45.9
Observations				
	Count (N)	6,555	9,140	15,695
	Customers (n)	383	191	574
	Monthly Obs. (T-bar)	17.11	47.88	27.34

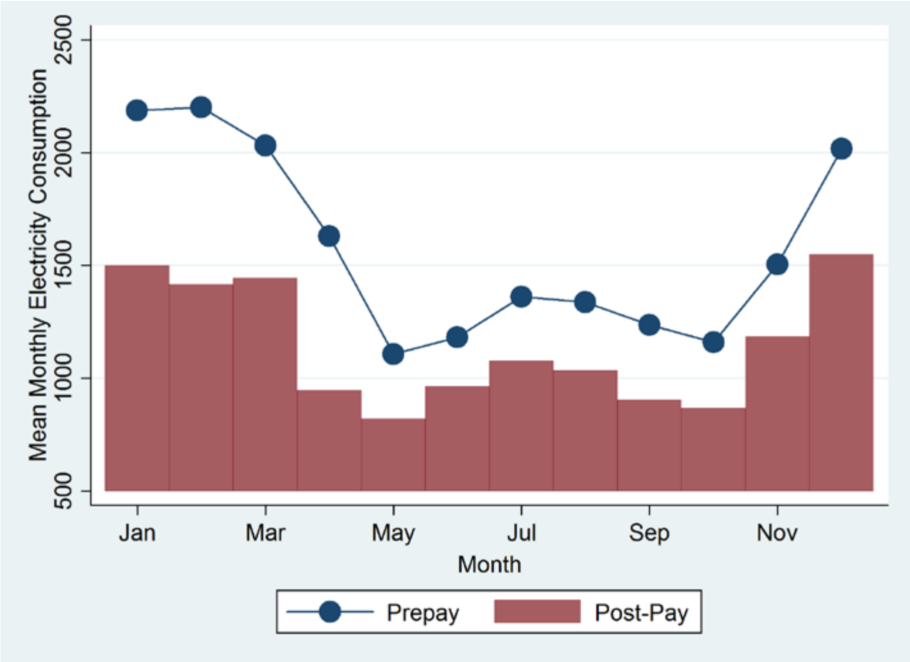
Once these changes were made, the complete data set used in the analysis contains 15,695 observations from 574 customers (see table 4.1). 191 of those customers are Jackson Electric members and the other 383 are members of the Bluegrass Electric Cooperative. On average, there were many more monthly observations from Jackson Electric customers than the customers from Bluegrass. Much of this difference can be explained by the fact that Jackson Electric started its program almost 15 months before Bluegrass. The average monthly electricity consumption is 1,737 kWhs for Bluegrass Electric customers, 1,497 kWhs for Jackson Electric customers, and 1,597 kWhs for the entire sample. Comparing participants and nonparticipants, we find that households that participate in prepay programs use significantly more electricity, on average, than customers that never enroll in a prepay program (see table 4.2).

Table 4.2 Comparing Sample to Postpay Customers

	Postpay	Prepay		
		Total	Before Enrollment	After Enrollment
Observations	7,828.00	15,695.00	9,080.00	6,615.00
Households	230.00	574.00	574.00	532.00
Mean Electricity Usage (kWh)	**1,158.11**	**1,597.00**	**1,708.83**	**1,443.10**
Mean ACDD	3.17	2.80	2.84	3.37
Mean AHDD	14.54	15.00	13.93	14.49

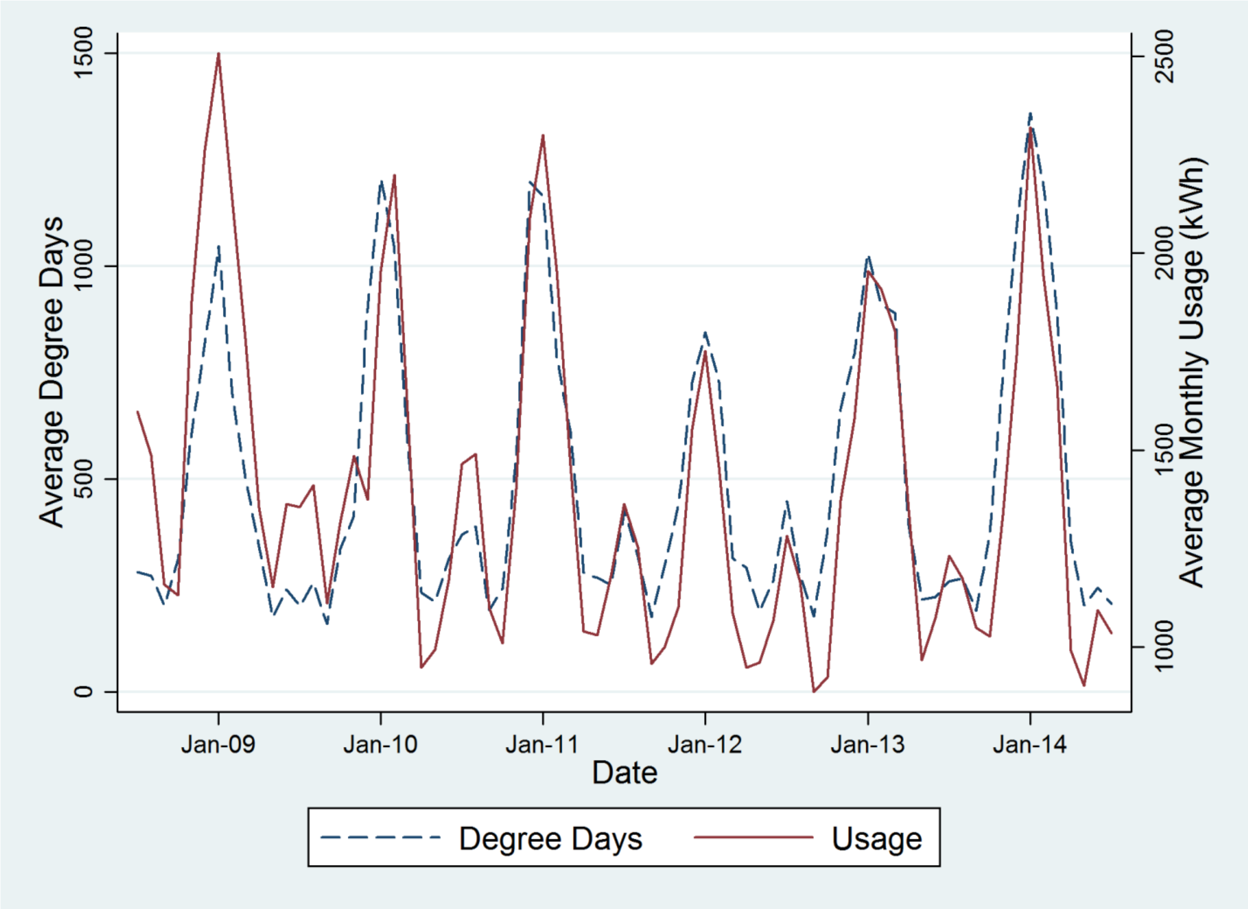
Figure 4.1 compares these consumption levels on a monthly basis. This dissimilarity is important to note because it implies that the households that enroll in a prepay program, which are the households that makeup our sample, are not necessarily representative of the large population of co-op members. We do not have any data that explains the reason for this large difference in consumption, but anecdotal evidence from the utilities suggests that an inefficient housing stock and electric heating are two of the most important factors (Carter & Claywell, 2014; Lakes, 2014; McCoun, 2014).

Figure 4.1 Comparing sample to non-prepay customers



One of the main drivers of electricity usage is weather. We combine weather data with the monthly usage data so that we can later control for its effect. We use weather data from the Midwest Regional Climate Center, which was compiled by the University of Kentucky College of Agriculture Weather Center. Separate readings are obtained for each utility service area. A centrally located airport is used as a corresponding weather station for each utility. Average cooling degree days (ACDD) and average heating degree days (AHDD) are the variables of interest for the analysis. Degree days are the difference between daily average temperatures and 65 degrees. Average temperatures are calculated by averaging the daily minimum and the daily maximum. CDDs are the number of degrees above 65 and HDDs are the number of degrees below 65. Average degree days refer to a monthly average of daily totals. The mean ACDD is 2.8, the mean AHDD is 15. Figure 4.2 shows how closely total degree days (CDD+HDD) align with the electricity consumption of the sample households.

Figure 4.2 Average monthly usage (kWh) and monthly degree days, 2008-2014



Chapter 5 Empirical Analysis

This section details the methods of analysis employed in this study. The analysis will focus on three primary questions: Do prepay customers change their consumption behavior after enrolling in a prepayment plan? If this effect exists, how does it vary seasonally? And does this participation effect diminish over time? We use a fixed-effects research design in which the identification of the behavioral response is based on a comparison of participants' consumption, before and after enrollment in the prepay program. The study contains three separate fixed-effects models to address each of the above questions.

In Chapter four, we discussed the fact that the treated group, the customers that chose to adopt prepay, show significantly different patterns of electricity consumption than the population as a whole. We assume that there is a strong self-selection bias with our sample as the participants made an endogenous decision to participate. Following Heckman's discussion of selection bias, this implies that a comparison of prepay customers with postpay customers would result in a biased estimate of the program's effect (Heckman, 1979). There are various methods to control for this effect, but they all require additional descriptive data that was unavailable for this analysis. To avoid the self-selection problem, we focus the analysis on a somewhat different question. Instead of treating prepay customers as a random selection of the larger population, we focus on how the participants change their consumption after enrolling in the program. Ozog uses a similar design to measure the impact of prepay on energy consumption (2013). He notes that this type of methodology is especially relevant for prepay programs, which are almost all voluntary (Ozog, 2013). In other words, utilities and other decision-makers are most interested in the effect on the customers that self-select into the program.

5.1 Fixed Effects Model

The fixed effects model is a simple linear regression model for panel data in which the intercept terms vary across all individuals, or households, in our case. The fixed-effects model can be specified as follows:

Equation 5.1

$$Y_{it} = \alpha_i + X'_{it}\beta + \varepsilon_{it}$$

Where Y_{it} is the monthly dependent variable, α_i is the unobserved individual-specific effect, $X'_{it}\beta$ is a vector of explanatory variables, and ε_{it} is the error term (Verbeek, 2012). The individual fixed-effect, α_i, captures all the time-invariant variation among the different households. In other words, we assume that all of the households in the model have varying characteristics that impact their consumption of electricity. This estimator attempts to control for that variation.

A random-effects model, which requires fewer degrees of freedom, would be a more efficient estimator than a fixed-effects model. The problem with this kind of model, however, is that the *x* value can be correlated to the error term, leading to biased and inconsistent estimators (Kennedy, 2008).
To test if this is the case in this analysis, a Hausman test is used. The Hausman test compares the random effects estimates to the unbiased fixed effects estimates (Kennedy, 2008). For all but one of the models below, we fail to reject the null hypothesis that the difference between the coefficients is not systematic, indicating that the random effects model is biased. We, therefore, conclude that the fixed effects model is more appropriate. Even in the case where the random effects model was not found to be biased, we still use the fixed-effects model for consistency. It is also worth noting that the estimates between the models are qualitatively very similar.

5.2 The Prepayment Effect

The empirical analysis begins with a simple model that attempts to isolate the effect of enrolling in the prepay program. To evaluate whether there is a change, we use a fixed effects model in which we regress a household's monthly electricity consumption, $Electricity\ Consumption_{it}$, on its decision to enroll in the prepay program, $Prepay_{it}$. We also control for weather variation and the individual co-op for which the household is a member. This model can be expressed in the following form:

Equation 5.2

$$Electricity\ Consumption_{it} = \alpha_i + \beta_1 Prepay_t + \beta_2\ ACDD_t + \beta_3\ AHDD_t + \varepsilon_{it}$$

Where the dependent variable, Y_{it}, is the monthly electricity consumption in kWhs for household *i* in month *t*; α_i is the unobserved individual-specific effect; $Prepay_t$ is a time-dependent dummy variable for whether the household is enrolled in the prepayment program in month *t*; and $ACDD_t$ and $AHDD_t$ are explanatory variables representing average cooling degree days and average heating degree days. We cannot include a separate variable for the household's co-op, because any variation associated with the different service territories is captured within the fixed effects estimator, α_i. The estimate of β_1 is the primary variable of interest as it indicates the change in consumption associated with participation in a prepay program. Any negative coefficient for this estimate will be consistent with the theory.

We also estimate a log-log specification of the model, and all other models discussed in this analysis. We chose to show only the linear model for several reasons. First, the linear models are a better fit for the data set. Secondly, we wish to be consistent with the literature on changes to electricity consumption. Jacobsen, for example, chose a linear over a log-log model for his analysis on the effect of building codes on electricity consumption (Jacobsen & Kotchen, 2011). We also find that both models produce results that are qualitatively similar. Finally, the results from the linear model are much easier to interpret. For example, it is impossible to extrapolate a precise, overall annual effect of the prepay plan from the β_1 coefficient of a log-log model. This is due to the nonlinearity of the model and the fact that there is so much variation among months of the year (Jacobsen & Kotchen, 2011).

5.3 Seasonal Variation of Prepay Effect

In order to further explore the relationship between the prepay rate and weather, an additional model is employed that interacts $Prepay_t$ with $ACDD_t$ and $AHDD_t$. The purpose of this model is to see how customers enrolled in the prepay program respond to weather variability, which is one of the primary drivers of electricity consumption (EIA, 2013).

Equation 5.3

$$Electricity\ Consumption_{it} = \alpha_i + \beta_1 Prepay_t + \beta_2 ACDD_t + \beta_3 AHDD_t + \beta_4 Prepay_t \times ACDD_t + \beta_5 Prepay_t \times AHDD_t + \varepsilon_{it}$$

This model follows the same form as Equation 5.2 except for the addition of two new interaction terms. These new variables, $Prepay_t \times ACDD_t$ and $Prepay_t \times AHDD_t$, will indicate how consumers respond to changes in weather when they are enrolled in the prepay program. We hypothesize that both coefficients will be negative and significant, indicating that an increase in degree days will result in a smaller increase in electricity consumption for customers that are enrolled in prepay as compared to postpay customers. In other words, it would imply that customers temper their demand for heating and cooling after enrolling in a prepay plan. A significant and negative coefficient for β_1 would imply that consumers use less electricity on prepayment plans, even when there is no heating or air conditioning requirement.

A second approach to the question of seasonal variability is to look at how the prepay effect varies across months of the year. To look at the question from this perspective, we create a new model in which monthly terms are added. The model is specified as follows:

Equation 5.4

$$Electricity\ Consumption_{it} = \alpha_i + \beta Prepay_t + \gamma Month_t + \delta Prepay_t \times Month_t + \varepsilon_{it}$$

In this specification, $Month_t$, is a dummy variable for each month of the year, excluding October. We use October as the baseline year because, on average, electricity consumption is lowest during that month. $Prepay_t \times Month_t$ is a new variable that interacts the month dummies with the prepay dummy. The δs are our variables of interest for this model. Similar to the model above, we hypothesize that summer and winter months will have significant and negative coefficients because we expect customers to use less heating and cooling when enrolled in a prepay plan. In this model, changes in temperature are partially captured within the monthly dummy variables, but it may be that there are other characteristics of the monthly variables that impact usage as well.

5.4 Backsliding

The final question we investigate is whether the length of time that a household has been enrolled impacts the prepayment effect discussed above. We begin with equation 5.3 and add a new continuous variable $Time_{it}$ that indicates how long (in months) a household *i* has been enrolled in a prepay plan.

Equation 5.5

$$\begin{aligned} Electric\ Consumption_{it} \\ = \alpha_i + \beta_1 Prepay_t + \beta_2 ACDD_t + \beta_3 AHDD_t + \beta_4 Prepay_t \times ACDD_t + \beta_5 Prepay_t \\ \times\ AHDD_t +\ \beta_6 Time_{it} + \varepsilon_{it} \end{aligned}$$

The variable $Time_{it}$ is calculated by subtracting the first month that the household was enrolled in a prepay plan from the current observation month. All observations prior to enrollment have a zero value for this variable. Based on existing literature, we expect that, if a significant effect exists, that it will be negative. Allcott and Rogers, for example, show that there is a pattern of “action and backsliding” in response to home energy reports that are intended to alter electricity consumption behavior (Allcott & Rogers, 2012). They also identify numerous other studies that show similar responses.

Chapter 6 Results

In this section, we will present the results of the fixed-effects models outlined in Chapter 5. The results of all four specifications can be found in table 6.1.

Table 6.1 Model Results

	5.2		5.3		5.4		5.5	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Prepay	-177.4***	(11.44)	20.25	(28.79)	11.47	(38.42)	-109.7***	(32.36)
ACDD	61.33***	(2.078)	68.81***	(2.540)			67.22***	(2.540)
AHDD	42.43***	(0.551)	47.16***	(0.724)			46.55***	(0.726)
PrepayXACDD			-17.50***	(4.405)			-13.78**	(4.415)
PrepayXAHDD			-10.35***	(1.107)			-9.248***	(1.111)
Time							4.550***	(0.522)
January					1285.1***	(31.90)		
February					1347.9***	(31.95)		
March					733.0***	(31.54)		
April					410.9***	(32.05)		
May					42.75	(32.90)		
June					181.8***	(33.65)		
July					353.1***	(33.77)		
August					377.1***	(33.84)		
September					165.6***	(33.90)		
November					345.3***	(31.82)		
December					789.6***	(31.94)		
Jan X Prepay					-31.34	(50.69)		
Feb X Prepay					-540.9***	(50.61)		
Mar X Prepay					-56.77	(50.22)		
Apr X Prepay					-388.8***	(51.32)		
May X Prepay					-154.9**	(51.27)		
Jun X Prepay					-141.9**	(51.11)		
Jul X Prepay					-138.8*	(54.30)		
Aug X Prepay					-253.3***	(55.92)		
Sep X Prepay					-238.5***	(55.12)		
Nov X Prepay					53.93	(51.81)		
Dec X Prepay					-48.16	(51.14)		
Constant	864.9***	(14.80)	776.0***	(17.91)	1129.3***	(23.24)	587.9***	(28.03)
R-sq: Within	0.342		0.346		0.335		0.350	
R-sq: Between	0.092		0.100		0.088		0.090	
R-sq: Overall	0.219		0.223		0.201		0.219	
N	15695		15695		15695		15695	
**** p<0.05, ** p<0.01, *** p<0.001***								

6.1 The Prepayment Effect

The results of our first model (equation 5.2) indicate that $Prepay_t$ has a significant and negative impact on household electricity consumption. Specifically, the model demonstrates that, all else being equal, a customer will consume 177.4 kWhs less after enrolling in a prepay program. This effect can also be expressed as an 11.1% decline when compared to our sample's monthly average consumption of 1,597 kWhs. This reduction is in line with our expectations, which are based on the theoretical models outlined in chapter 3.

As expected, both $ACDD_t$ and $AHDD_t$ were significant and positive. All else being equal, a one degree increase in average monthly cooling degree days results in 61.33 kWh increase in electricity consumption. Similarly, a one degree increase in average monthly heating degree days results in a 42.43 kWh increase. Multiplying these results by the sample's average CDDs and HDDs provides an interesting way to think of these results. We find that consumption linked to CDDs represent about 10.7% of annual consumption. HDDs, meanwhile, can explain nearly 40% of the samples average annual consumption. This is further evidence of the importance of heating to total electricity use in the service territories represented in our sample.

We do not have data that indicates how consumers are tempering their demand. It could be that they are changing their behavior, doing things like raising their thermostat in the summer and lowering it in the winter. This would, in effect, be a decrease in overall demand for energy services. Conversely, customers could be making investments in insulation or better appliances that could allow them to heat and cool their home more efficiently. Without additional data or a follow-up survey, understanding the "how" aspect of this question is beyond the scope of this paper.

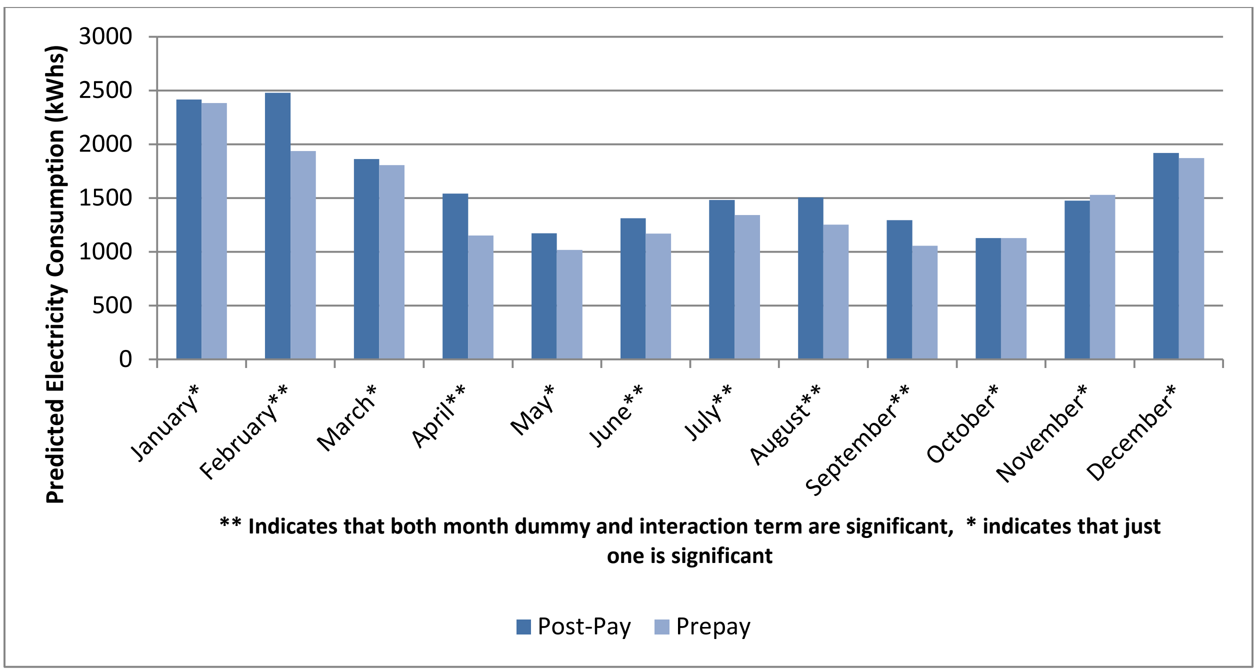
6.2 Seasonal Variation of Prepay Effect

We use two different models to investigate the question of how the prepay effect varies seasonally. In the first model (Equation 5.3), $Prepay_t$, by itself, is insignificant. To understand why this might be the case, it makes sense to first explain the other coefficients in the model. As in the model above, $ACDD_t$ and $AHDD_t$ were significant and positive, indicating that consumption increases by 68.81 and 47.16 kWhs, respectively, as average degree days increase by one. What makes this model different is the addition of the interaction terms, $PrepayXACDD_t$ and $PrepayXAHDD_t$. Both of these terms are found to be significant and negative. To be interpreted, they must be combined with the $ACDD_t$ and $AHDD_t$ coefficients. For example, a one degree increase in ACDDs implies that a postpay customer will, on average, consume an additional 68.81 kWhs. To measure the average change in consumption for a prepay customer, however, one must combine $ACDD_t$ and $PrepayXACDD_t$. In this case then, a prepay customers consumption would, on average, change by 68.81 kWhs minus 17.50 kWhs, resulting in a total change of 51.31 kWhs. Similarly, in response to a one degree increase in AHDDs, a prepay customer would increase their consumption by 47.16 kWhs minus 10.35 kWs, resulting in a total increase of 36.81 kWhs.

As was mentioned in chapter 5, we can interpret the negative coefficients on the interaction terms as a sign that customers temper their demand for heating and cooling after enrolling in a prepay program. How, then do we interpret the insignificance of the $Prepay_t$ coefficient? This implies that, in the absence of degree days, there is no significant difference between a customer's consumption before and after enrolling in a prepay plan. One theory of why this might be the case is that total energy costs for such mild periods are so low that the customer has less incentive to change behavior. Another theory is that changing the way one consumes heating and cooling energy services is simply the most effective way to reduce consumption. Again, we do not have any information that answers the "how" aspect of this change. The takeaway message of this model is that the prepay effect is more pronounced during periods of high or low temperatures than during mild weather.

We estimate a second model (Equation 5.4) to investigate the question of how the prepay effect varies seasonally. Instead of heating degree days, this model uses monthly dummy variables as well as monthly interactions with the $Prepay_t$ variable. Overall, we found that the $Prepay_t \times Month_t$ variables are not as significant as $PrepayXACDD_t$ and $PrepayXAHDD_t$ at measuring how consumer behavior varies throughout the year. As table 6.1 shows, all of the monthly dummy variables are positive, and all but the month of May are significant. We expected a positive sign on these coefficients as we chose to use October as a reference month because it had the lowest average electricity consumption. Most, but not all of the interaction terms are significant and negative. Like the model above, one must combine the interaction term with the monthly dummy in order to interpret these coefficients. Using April as an example, a postpay customer consumes an average of 410 kWhs more than in October. Once they switch to prepay, however, that difference decreases by 389, resulting in a total consumption level that is 21 kWhs higher than the reference month. To help explain the results of this model, we created a bar graph (Figure 6.1) that compares the model's predicted electricity consumption for a postpay consumer and a prepay consumer. The graph is more effective at showing that, even as consumption moves up and down with the seasons, customers enrolled in prepay almost always consume less electricity.

Figure 6.1 Predicted Electricity Consumption Based on Model 5.4



Due to the limited years of observations, we caution taking too much meaning from the monthly variations illustrated by this model. Months are not as effective as degree days at capturing seasonality because the weather can vary so dramatically from year to year. The results of this model, then, are sensitive to the specific years of observations in the sample. It could be that there are additional insights captured by monthly dummies, but it appears that the coefficients track very closely to what one would expect based solely on that month's average temperature. We therefore conclude that degree days are a much better indication of the seasonality of the program's effect.

6.3 Backsliding

The results of our final model show that, in addition to the prepay effect varying seasonally, it also diminishes over time. This last model (Equation 5.5) is the same as Equation 5.3 except for the addition of the variable $Time_{it}$, which we find to be positive and significant. This means that, all else being equal, every additional month that a customer is enrolled in a prepay program leads to a 4.55 kWh/month increase in consumption. Put another way, the coefficient for $Prepay_t$ shows that consumers use 109.7 kWhs less after enrolling in the program. The $Time_{it}$ coefficient implies that this reduction decreases by 4.55 kWhs for every additional month that the customer is enrolled. This result matches our expectations, which are based on the well-researched theory that many behavior-focused programs show signs of backsliding over time. A larger period of observation would allow us to determine if this effect is consistent in the long-term, implying that the prepay effect would eventually diminish to zero. The short time frame in this analysis, however, precludes this type of analysis.

As mentioned above, the prepay coefficient is -109.7 and is found to be significant. This result runs counter to the results from Equation 5.3, which was discussed in section 6.2. We expect that the $Time_{it}$ variable has produced a more realistic model because the averaging that occurs in model 5.3 is hiding the difference between newly enrolled customers and those that have been enrolled for a long period of time. For example, imagine a month with zero average HDD or CDD. While model 5.3 indicated that there was no significant difference between prepay and postpay consumers on average, model 5.5 suggests that a newly enrolled prepay customer will use significantly less electricity. This difference will then diminish over the time period that the customer is enrolled.

The coefficients on the interaction terms $PrepayXACDD_t$ and $PrepayXAHDD_t$ are very similar to the results from equation 5.3. Combining these coefficients with the $ACDD_t$ and $AHDD_t$ coefficients, we find that prepay customers increase their consumption by 53.44 kWhs per month or 37.30 kWhs per month in response to a one degree change in ACDDs or AHDDs, respectively. Postpay customers, on the other hand, increase their consumption by 67.22 or 46.55 in response to the same change in weather. When the coefficients of all of the variables are used to estimate consumption, we find that households decrease their monthly consumption by a range of 9-20% after enrolling in the program[17]. The largest decrease occurs for customers that have recently enrolled, during months of high ACDD. The smallest decrease occurs during mild months for customers that have been enrolled for a long period of time.

In all four models, we consistently find that the sample of prepay customers consume less energy after enrolling in the prepay program. We also find that that this effect varies with the weather, and that the effect diminishes over the length of time that the customer is enrolled. In Chapter 7, we will discuss some of the theoretical and practical implications of these results as well as some of the model's limitations.

[17] We estimated usage for new users (1st month of prepay) and experienced users (enrolled for 12 month) in mild months (no degree days, high ACDD months (10ACDD), and high AHDD months (30 AHDD).

Chapter 7 Conclusion

7.1 Summary of Results

The purpose of this study is to investigate the relationship between prepayment and the consumption of electricity. Using household level monthly usage data from customers that enroll in a prepay program, we employ a fixed-effects model to see if there is a change in electricity consumption after enrollment. The results of our model indicate that prepay customers reduce their consumption by an average of 11.1% after enrolling in the program. We also find that this response is larger during periods of high or low temperatures than during mild weather. Furthermore, we find evidence that the prepayment effect diminishes over the length of time that a customer is enrolled in the program.

In order to understand the significance of an 11.1% decrease in electricity consumption, it's useful to give the effect some context. As a comparison, the three investor owned utilities[18] (IOUs) in KY spent a combined $24.83 million in 2010 on residential DSM. The sole purpose of this expenditure was to help consumers reduce their electricity consumption, but it's total impact was only a 0.5% drop in electricity consumption for the year (Neubauer & Elliott, 2012). Even states that have energy efficiency requirements typically only require an annual 1-1.5% savings. An oft-cited triumph in behavior-based conservation is the home energy report issued by the company OPOWER. These reports have been extensively studied and were found to cause a 2% decrease in consumption, on average (Allcott, 2011). Even updating state building codes doesn't achieve the same level of impact as was found with prepay rates. Comparing homes constructed immediately prior to the change and those constructed immediately after the change, Jacobsen found that updated building codes in Florida lead to a 4% decrease in electricity consumption and a 6% decrease in natural gas consumption (Jacobsen & Kotchen, 2011). The authors understand that all of these programs are unique, and that the results of this analysis may only apply to a subset of customers. The purpose of these comparisons is simply to demonstrate that an 11.1% decrease is very large in the world of electricity consumption.

[18] Data was unavailable for DSM programs at the RECCs in this report. 2010 is the most recent DSM data available that is specific to KY.

Chapter two proposed possible theoretical explanations for why consumption might change simply by changing the method by which someone is billed. We noted the importance of bounded rationality and status-quo decision making, and how these limit one's ability to alter their consumption pattern. We also pointed out the dichotomy between one's *planner* and *doer* self, and how short term desires often prevent consumer from making long-term rational decisions. We suggested that prepay plans could alter this model because of the feedback they provide as well as the constraint they place on what was perfectly liquid consumption. This study produces strong evidence that suggests that the typical model for electricity demand is insufficient at explaining these behavioral factors. We do not, however, produce enough evidence to isolate the specific components that are missing from the model.

While we haven't determined the exact mechanism that causes the change in electricity consumption, providing evidence that there is a change is significant. These results add to the existing literature on the determinants of electricity consumption, giving analysts and planners an additional tool to model end-use consumption. In the introduction, we mentioned that prepay rates could be used as a new tool to lower overall residential electricity consumption, similar to DSM programs. In order to demonstrate that this could be a viable policy option, one would have to produce evidence that the prepay effect applies to the population as a whole. Due to limitations on the data that were available, our research, while suggestive, does not meet this standard. However, given that prepay programs are almost all voluntary, it is useful in the sense that there will always be a self-selection bias for the customers that choose to enroll in these programs. In other words, it could be argued that utilities that have similar customer populations and similar program costs could see similar results for the customers that self-select into their programs.

As with any new program, there are costs and benefits. In the case of prepay programs, the customers, the utilities, and the wider society are all impacted. In the following section, we will address the potential costs and benefits to the consumer. We addressed some of the potential costs and benefits to the utilities in chapter 2. Arguably, prepay and postpay should coexist because each plan has benefits for different types of customers. A simple analysis of financial records would allow researchers to determine how prepay programs impact total sales, total fees collected, and total debt write-offs. With the results of this analysis, we can assume that the utilities will see a small decrease in total sales, but we do not have the evidence necessary to address the other issues. Finally, there is a benefit to society in the form of the emissions reductions. Conserving electricity decreases CO_2, a greenhouse gas, as well as SO_2 and NO_x, which are known to cause health problems. Appendix A calculates the total saved energy and the total emissions reductions for 2013 based on the results of this analysis.

7.2 Policy Implications: Consumer Costs

One of the main disputes about the use of prepay rates is how much they actually cost electricity consumers. Consumer advocates often argue that prepay program fees add up, resulting in higher charges to consumers who are most sensitive to electricity costs (Garthwaite, 2014; Howat, 2012; Villarreal, 2012). Utilities counter that the programs give consumers the ability to save money by controlling their electricity usage. They also point out that these consumers can save by avoiding expensive late-payment fees.

To help resolve the debate, we do a brief analysis of costs from the perspective of the average consumer in our sample. Based on the mean monthly electricity consumption of 1,597 kWhs, we look at four different reference cases to estimate a consumer's postpay annual costs and four scenarios to see how those costs change after enrolling in a prepay program. Table 7.1 describes those scenarios and equation 7.1 shows how total annual costs are calculated.

Equation 7.1

$$
\begin{aligned}
&Total\ Annual\ Costs^{19} \\
&\quad = (Electricity\ Consumption(kWh) \times Rate) + Fixed\ sercice\ charge \\
&\quad + Fixed\ prepay\ charge + transaction\ fees^{20} - avoided\ fees(\text{late fees} \\
&\quad + \text{disconnection fees})
\end{aligned}
$$

[19] For simplicity, we exclude taxes and riders from this calculation. They are a small portion of the monthly bill and are the same for both types of customers.

[20] Only one of the two utilities charges a transaction fee, but we include it to show its impact on total costs.

Table 7.1 Cost Scenarios

	Usage	Late Fees	Disconnects	Payments/ month
Reference Case 1	Average	None	Zero	NA
Reference Case 2	Average	2 months	Zero	NA
Reference Case 3	Average	4 months	One	NA
Reference Case 4	Average	6 months	Two	NA
Scenario 1	Average	NA	NA	1
Scenario 2	Average	NA	NA	5
Scenario 3	11.1% Decrease	NA	NA	1
Scenario 4	11.1% Decrease	NA	NA	5

Table 7.2 Scenario Results: Total annual costs and percent difference

		Reference Case 1	Reference Case 2	Reference Case 3	Reference Case 4
	Total Cost	**$1,887**	**$1,904**	**$1,966**	**$2,029**
Scenario1	**$1,960**	**3.85%**	**2.92%**	**-0.33%**	**-3.38%**
Scenario2	**$2,030**	**7.56%**	**6.60%**	**3.23%**	**0.07%**
Scenario3	**$1,759**	**-6.82%**	**-7.66%**	**-10.57%**	**-13.31%**
Scenario4	**$1,834**	**-2.84%**	**-3.72%**	**-6.76%**	**-9.61%**

Table 7.2 shows the total cost results of the four scenarios and how they compare to the four reference cases. We find that prepay programs save customers money in any scenario in which one accounts for the 11.1% reduction in demand that we calculated from the empirical analysis. On the other hand, if you don't account for any change in usage, it is likely that a consumer's total electricity costs will be higher if they are enrolled in a prepay program. This is from the obvious fact that prepay plans add an additional monthly fee. However, reference cases 3 and 4 show that it is possible that late fees and disconnection fees can outweigh the prepay program fees. It is also worth noting that transaction fees can add up to a significant costs when consumers make numerous payments per month. The results of this

simple analysis demonstrate that the question of costs is more complicated than many make it seem. It can be the case that consumers save money with prepay, but the opposite can also be true. What is clear is that regulators should not be quick to dismiss prepay plans for cost reason because they can allow many cash-constrained customers to save money and avoid debt.

7.3 Suggestions for Further Research

The results of this paper suggest that a customer's billing method could have an important impact on their consumption. However, much work remains to be done to get a better understanding of this relationship. Most importantly, a similar analysis to this one that incorporates descriptive information about the households would produce results that could be applied to the population as a whole. Additional studies would also benefit from a customer survey. This would give researchers a better idea of how and why consumers alter their consumption choices. Finally, to isolate the impact of the rate structure from the feedback, researchers could conduct a similar analysis that includes a control group of postpay customers that have access to the same form of feedback as the prepay customers. As electricity costs continue to rise and the need to reduce consumption continues to grow, these questions will only become more important in the future.

Appendix A: Environmental Costs

In order to provide an estimate of the social benefits of emissions reductions, we first estimate the total saved energy for 2013 based on the total number of prepay customers at Bluegrass Energy and Jackson Electric, the average consumption for prepay customers, and the estimated reduction in consumption (see table A.1). Based on these inputs, we estimate that prepay customers at these two coops saved 377 MWhs of electricity that would otherwise have been generated.

A.1 Total Electricity Saved, 2013

Average Electricity Consumption			Saved Electricity		
Monthly (kWh)	Annual (kWh)	Total Prepay Customers	Percent Reduction	Total Saved Energy (kWh/year)	Total Saved Electricity (MWh/year)
1,597	19,164	1,772[21]	11.1%	376,940.55	376.94

We then use the estimated electricity saved to calculate total emissions reductions in terms of CO_2, SO_2, and NO_X. In order to calculate these emissions, we obtain net emissions rates[22] for Eastern Kentucky Power Cooperative[23] from the EPA Air Markets Program data (*EPA Air Markets Program Data*, 2013)[24]. Table A.2 shows the total emissions reductions attributed to the saved energy from prepay programs.

A.2 Emissions Reductions

	Net Rate	**Emissions (Rate*Total Saved Electricity)**	
Unit	*lbs/MWh*	*lbs.*	*Metric Tons*
CO_2	2,048.47	772,152.2	350.24
SO_2	2.05	774.31	0.351
NO_x	0.92	346.43	0.157

Avoided emissions produce a significant benefit to society. CO_2 is a greenhouse gas, which contributes to climate change. Meanwhile, reducing SO_2 and NO_x produces many health benefits as their

[21] Total active prepay customers at Bluegrass Energy and Jackson Electric.
[22] We use net rates because it takes into account the losses from parasitic loads such as scrubbers and distribution losses.
[23] Eastern Kentucky Power is the electricity generator for both co-ops.
[24] In Kentucky, this data is collected and maintained by the Energy and Environment Cabinet.

concentration in the air is linked to many illnesses (EPA, 2014). Calculating the exact societal costs and benefits is beyond the scope of this paper, but we include them in this paper to note their importance. Refer to the EPA’s most recent Regulatory Impact Analysis for an example of how these pollutants can be monetized in a benefit/cost analysis (EPA, 2014).

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